Social Pensions for Greying India

Empirical Analyses of Potential Effectiveness Constraints

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Acknowledgments

My interest in development economics was sparked almost 10 years ago when Prof. Stephan Klasen's teaching at the University of Göttingen made me aware of this fascinating sub-field of economics. Ever since the first classes in Growth and Development it was clear to me that I wanted to pursue a career in this area and I subsequently participated in numerous development economics classes and seminars. Later he facilitated my first steps on this career path by supporting my applications for a semester abroad at Delhi School of Economics and for an internship with the German Development Cooperation (GIZ). He finally also supported my application for the PhD at the University of Zurich and I am thankful to him for having believed in my capabilities to pursue a career in development economics research.

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Summary

Old-age poverty is increasingly a concern in developing countries that face accelerating demographic change, widespread informal sector employment and high rates of rural-urban migration. As a potential remedy, social pensions are designed to mitigate old-age poverty. Social pensions as cash transfers to the elderly are in many countries targeted towards the elderly poor to support those who cannot rely on formal sector pension schemes and have insufficient means to satisfy their basic needs. The effectiveness of social pensions remains generally under-researched and we lack knowledge of the various factors that potentially constrain the effectiveness of social pensions.

This dissertation addresses this knowledge gap by examining two potential effectiveness constraints. The poverty-reducing impact may be limited if the intended beneficiaries do not receive the benefits or if the public support provided by the government crowds out private support. While studies exist on mistargeting of social transfers and crowding out effects more generally, in the presence of demographic change, the elderly represent an increasingly important group in the population that requires attention. Given their physical constraints and lower education levels, the elderly represent a hard-to-reach target group and might show different behavioral reactions to social policies and reforms. Therefore, insights from other studies on mistargeting of social transfers and crowding out cannot be directly applied to the elderly. The empirical analyses presented in this dissertation focus on the Indian context where demographic change is accelerating, poverty and informal sector employment are widespread and relevant social pension reforms were implemented in the late 2000s. I combine nationally representative panel data from the India Human Development Survey (IHDS) with extensive administrative information on eligibility rules to examine these potential effectiveness constraints.

After an introduction in Chapter 1 and general background information in Chapter 2, Chapter 3 focuses on the question whether social transfers should be targeted or universal.

This debate is particularly relevant for the implementation of social protection schemes in developing countries. While the limited availability of public resources encourages targeting, the difficulty to identify the poor calls for a universal allocation of benefits. To contribute to this debate, this chapter examines the targeting performance of and access to social pensions for India's elderly poor. The results show that during the time period of social pension reforms, exclusion and inclusion errors were successfully reduced but the exclusion of elderly poor continues to be extremely high. Comparing the existing targeting approach to a hypothetical random allocation, I show that the difference between targeting errors from random allocation and actual targeting errors is limited. The reforms aimed at increasing the transparency of social pension allocation and the empirical results confirm that the Below Poverty Line ration card has become the most important determinant of access to social pensions. However, this focus on the ration card promoted by the national government has its own weaknesses. Non-poor elderly exploit the unwarranted possession of this ration card and results suggest that in the time period after the reforms individuals with direct connections to local government officials are more likely to access social pension benefits compared to those elderly who lack these personal connections. The current targeting approach seems to be beneficial for well-connected older people while many elderly poor typically lacking these connections lag behind.[1]

Focusing on official targeting errors, Chapter 4 examines whether transparency in eligibility rules for the implementation of social programs could be an effective measure to reduce mistargeting. While prior studies have examined the relevance of transparent delivery mechanisms, together with co-authors, I focus on the transparency of eligibility criteria that can be reformed at relatively low cost. India's social pension reforms in the late 2000s provide the opportunity to examine the effect of a change in these criteria within and across states. Using two rounds of the India Human Development Survey along with extensive administrative information collected for the different states, we test whether increasing the transparency of eligibility criteria reduces the mistargeting of social pensions. We thereby allow for a tolerance band, and account for changes in social pension coverage. Our results confirm the expected relationship between the transparency of eligibility criteria and targeting performance and are robust to different specifications of the transparency measure and various robustness checks. Since eligibility criteria can be

1 This chapter is based on a single-authored paper that has already been published online on the journal's website and will be published in print as Asri, Viola (2019). Targeting of social transfers: Are India's poor older people left behind? *World Development*, 115 (March 2019), 46-63.

changed at low cost, this suggests a viable route for reform in many developing countries.[2]

As governments in developing countries have been expanding cash transfers targeted towards the elderly poor to mitigate old-age poverty, another relevant concern is that the expansion of public transfers could crowd out private support. In Chapter 5, I examine this concern for social pensions in India where coverage improved substantially in the late 2000s. Since coresidence can be seen as one proxy for informal support, I use again IHDS data from 2004-05 and 2011-12 to track a sample of elderly individuals during a time-period of social pension reforms examining how social pension receipt affects their coresidence with own working age children. In a first step, I account for individual level heterogeneity and relevant covariates at the individual, household and village level. Yet, as social pension receipt itself can be influenced by coresidence with working age children, I exploit state-specific administrative rules on age-based eligibility to use two-stage least squares estimation addressing these concerns of reverse causality. The empirical results suggest that receiving social pensions reduces the likelihood of living with working age sons. The results are robust to using an alternative instrument and are not sensitive to excluding any Indian state. Overall, this chapter shows the importance of taking into account unintended behavioral responses of other household members, too, when reforming social pensions to further reduce old-age poverty in developing countries like India.[3]

This dissertation contributes thematically and methodologically to the existing literature by enhancing our understanding of the limited effectiveness of social pensions in the Indian context. Based on the findings of the three studies presented in this dissertation, I conclude by deriving policy implications for future reforms and suggesting relevant avenues for future research.

2 This chapter is based on a working paper that has been co-authored with Katharina Michaelowa, Sitakanta Panda and Sourabh B. Paul. The current version is available upon request.

3 This chapter is based on a single-authored working paper available upon request.

1

Introduction

The case for social protection is compelling. It is both a human right and a sound economic policy. Social protection contributes to alleviating poverty, exclusion and inequality, thus strengthening political stability and improving social cohesion. As reflected in international labor regulations and human rights, the right to income security in old-age involves the right to receive a social security pension. However, as shown by a recent report of the International Labour Organization, almost 50 percent of all people in retirement age worldwide do not receive a pension (ILO 2014, p.73). Since contributory schemes are inadequate for large parts of the population in developing countries (e.g. due to a high share of informal sector workers with low and fluctuating incomes), governments in many middle- and low-income countries have made great efforts to establish non-contributory pensions to guarantee basic income security in old age to all in recent years (ILO 2014; Barrientos 2009; Hagemejer & Schmitt 2012).

Non-contributory pensions, or so-called social pensions, specifically address old-age poverty. They are particularly relevant for developing countries with high rates of informal sector employment and chronic poverty but their effectiveness remains under-researched. While a few primarily descriptive studies exist on the effectiveness of social pensions (Chopra & Puddussery 2014; Gupta 2013; Kaushal 2014), we lack knowledge on the factors constraining the effectiveness of social pensions. This dissertation focuses therefore on improving our understanding of two potentially relevant constraints: First, a weak targeting performance might cause that eligible individuals do not receive the benefits and ineligible individuals do. Second, as in developing countries social pension amounts tend to be low and elderly depend on family support, crowding out of private support can make social pensions less effective in reducing old-age poverty. For instance, if the receipt of social pension benefits induces a reduction of informal support by family members, e.g. through reduced coresidence, the poverty-reducing impact of social pensions may be constrained.

India is an important case in point. Recognizing the need for social pensions, in 1995 the national government launched the National Old Age Pension Scheme as part of the National Social Assistance Programme administered by the Ministry of Rural Development. While social pension coverage and benefit of this non-contributory social pension scheme was very low in the initial years, social pension coverage and amount increased substantially later on with major reforms being implemented in 2006 and 2007.

In this thesis, I examine both potential constraints and focus on the Indian context because demographic change is accelerating quickly, poverty is widespread and social pension amounts compared to other countries relatively low. At the same time, implementation challenges appear to be particularly severe. Learning more from a challenging context like India can therefore provide insights that can also be applied to other countries. Literature in this area is relatively scarce with only few quantitative studies. I contribute to this scarce literature by conducting the empirical analyses with the first nationally representative panel data set for the Indian context which enables me to extend the range of previously used methodologies using panel regressions, instrumental variable estimation and various robustness checks.

Chapter 2 provides general background information on social pensions in the Indian context. Chapter 3 focuses on the targeting problems as a potential constraint and analyzes from a poverty reduction perspective whether the elderly poor are left behind and which factors are relevant for access to social pensions. Chapter 4 takes a different perspective on the targeting performance. Apart from the poverty-reduction objective that defines who should receive social pensions and who should not, from a normative human rights perspective, governments also define more specific official targeting rules with more or less concrete indicators. Whether those official rules are applied in practice determines whether those who are officially eligible receive social pensions. There can be large discrepancies between policy formulation and implementation. Whether and how these discrepancies can be mitigated by making eligibility criteria more transparent and more easily verifiable is the focus of this chapter which is based on a joint paper with Katharina Michaelowa, Sitakanta Panda and Sourabh B. Paul.

Chapter 5 examines a different important potential constraint. Closely linked to political debates regarding social welfare schemes, the research question for Chapter 5 is whether social pensions induce a crowding out of family support proxied by coresidence. If working age children tend to leave the household when elderly receive social pensions, this can imply that the allocated cash transfer cannot mitigate poverty effectively since at the same time their children might reduce private support. As social pension amounts are in general very low in India, this could even imply that the elderly are worse off when they receive the social pension but lack the private support from their adult children.

2

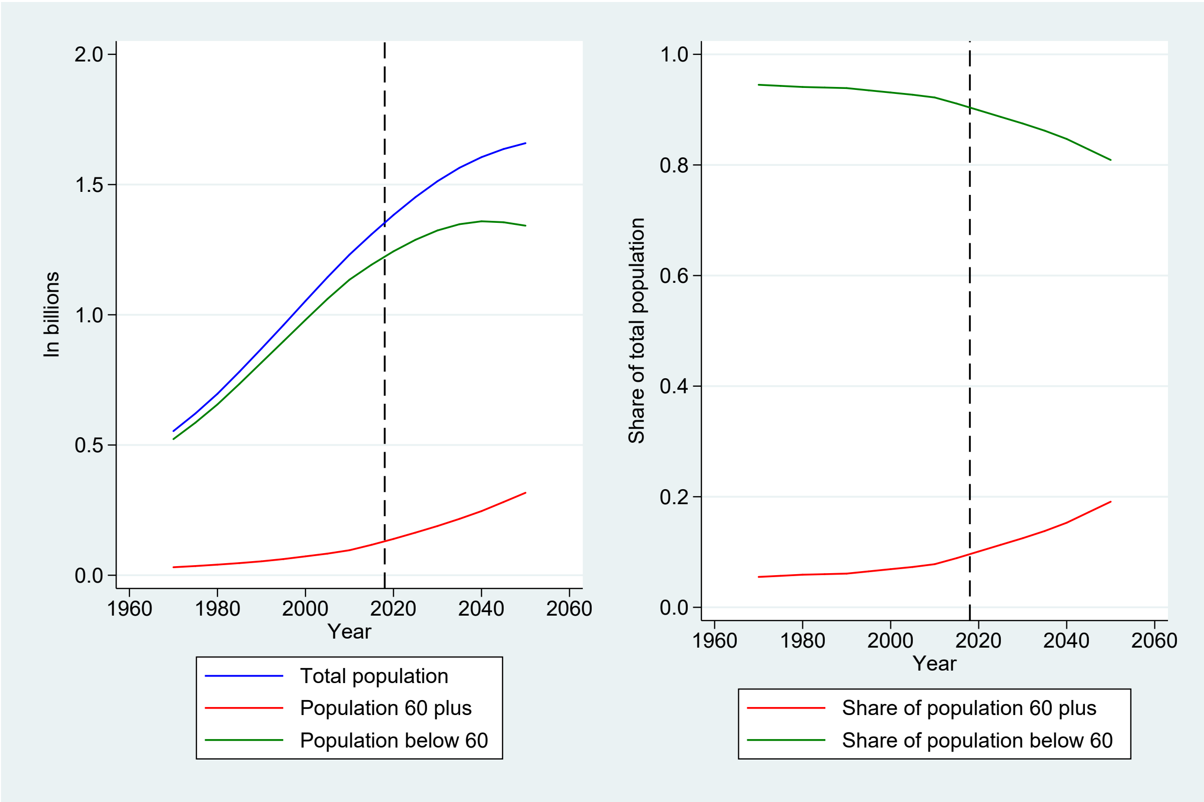
Background: The Need for Social Pensions

Accelerating demographic change, a persistently large informal sector and weakening family support for the elderly have important implications for old-age poverty in developing countries. Multi-generational household models that traditionally provided support to elderly are diminishing due to migration and declining fertility (e.g. James 2011). In contrast to the small minority of formal sector workers that benefit from comprehensive social protection and old-age income security, the vast majority of informal sector workers is predicted to face increased risks of old-age poverty in the near future given their lack of social protection coverage (e.g. Lloyd-Sherlock 2000). As mentioned above, implemented as cash transfers, social pensions aim to mitigate old-age poverty faced by individuals who lack social protection coverage (Holzmann & Hinz 2005). To improve the old-age income security of the poor, in 1995, the Indian government introduced the National Old Age Pension Scheme (Government of India 1998).

The need for an effective social pension scheme in India has been reinforced by progressing demographic change. As presented in Figure 2.1, for the time period of 2010 to 2050, India's population aged 60 years and older is expected to triple (from 96 million to 316 million) while India's population of individuals aged younger than 60 years is expected to grow only by 18 percent (from 1.134 billion to 1.342 billion). After 2050, the United Nations World Populations Prospects 2017 even predict a decrease in the absolute size of the population younger than 60 years of age while the population aged 60 years and above is expected to continue growing. The fact that India's population is ageing is also reflected in the relative shares of the population groups (see Figure 2.1). While the share of India's population aged 60 years and older is predicted to continue increasing in the next decades, the opposite is the case for the share of India's population aged younger than 60 years (United Nations 2017).

The fact that more than 90 percent of the labor force is working in the informal sector implies that the vast majority of elderly lacks social protection in old-age from which only a small minority of formal sector workers benefits (ILO 2018). Given widespread poverty, many of them also lack adequate savings and their well-being in old-age depends essentially on governmental support beyond the support that their families can provide.

Figure 2.1: Demographic change in India



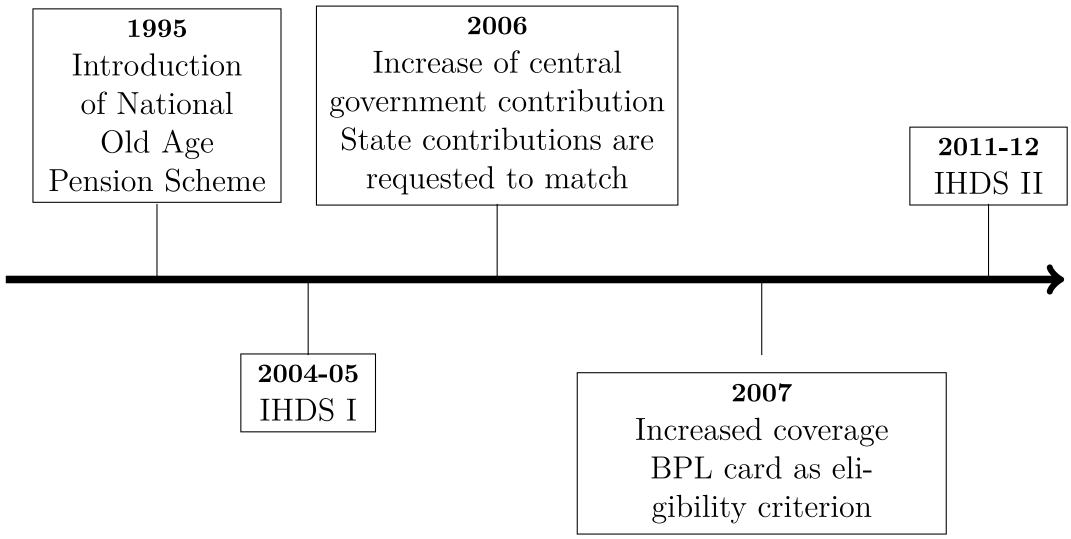
Source: Author's illustration, data from United Nations (2017).

The Ministry of Rural Development is in charge of the national social pension scheme but the state governments are responsible for the implementation through panchayats (i.e. village councils) in rural areas and municipalities in urban areas, as stated in the government guidelines of 1995 (Government of India 1998, p.4). Over time, reforms aimed at increasing the social pension amount as well as the coverage. In 2006, the central government contribution to the social pension amount was increased from 75 INR to 200 INR per month and the central government requested all state governments to match the central government contribution (Government of India 2006). In terms of purchasing power, 75 INR corresponded to 6.8 international $[1] in 2005 and 200 INR corresponded to 12.5 international $ in 2012 (World Bank 2016c). As described in more detail in Kaushal (2014), even several years after the reform, in 2011-12 many state governments do not match the central government contribution. Even if they do, the total social pension amount remains substantially below the Indian poverty line being 447 INR (ca. 40.4 international $ in rural India and 579 INR (52.4 international $) in urban India in 2004-05 and 816 INR (51.0 international $) in rural India and 1000 INR (62.4 international $) in urban India in 2011-12 (Reserve Bank of India 2013). As shown by HelpAge International in a database on social pensions, compared to other countries that have means-tested targeted social pension schemes, social pension amounts in India are very low. For instance South Africa's old-age grant is about 107 international $ and Brazil's social pension amount is about 300 international $ (HelpAge International 2015). Similar to the described increase in the pension amount, the coverage of India's national social pension scheme tripled from almost 7 million beneficiaries in 2002-03 to 23 million beneficiaries in 2014-15 (Government of India 2014).

The timeline in Figure 2.2 gives an overview of the relevant national reforms as documented in official government documents and the India Human Development Survey (IHDS) data collection periods.

1 International $ is used here and elsewhere in this dissertation to indicate values adjusted for differences in purchasing power. In contrast, values stated with their currency such as INR and USD indicate values that are not adjusted for differences in purchasing power.

Figure 2.2: Timeline of national social pension reforms and IHDS data collection



Source: Author's illustration based on Government of India (1998) and Government of India (2007).

3

Targeting of Social Transfers: Are the Elderly Poor Left behind?

3.1 Introduction

The effectiveness of social pensions in terms of old-age poverty reduction depends essentially on whether social pensions reach the elderly poor or not. However, the targeting performance remains an under-researched topic in India. Existing studies do not focus on the targeting performance and suffer from different limitations. Dutta et al. (2010) and Gupta (2013) analyzed the implementation of social pensions in a descriptive manner for a few selected states. Chopra & Puddussery (2014) assessed the implementation of social pensions but focus in their analysis on beneficiaries and lack data on non-beneficiaries and hence cannot assess the targeting performance in a comprehensive manner. The latest study by Kaushal (2014) used repeated cross-sectional data for all of India but lacked information on social pension receipt and needed to approximate beneficiary status. Research on social pensions in other countries including Brazil and South Africa has made the importance of social pensions for poverty reduction evident. The impact of social pensions is not restricted to the well-being of direct beneficiaries; other household members and especially grandchildren seem to benefit as well from the cash transfer (Duflo 2000; Edmonds et al. 2005; Lloyd-Sherlock 2006).

This chapter contributes to the existing literature in two ways: First, improving our understanding of whether social pensions reach the elderly poor is an important contribution for analyzing the effectiveness of social pensions in India and other developing countries with similar institutions and similar targeting challenges. Second, methodologically I contribute to existing targeting studies by comparing indicators of the targeting performance to a hypothetical random allocation of social pensions. As targeting errors appear to be very high and at the same time resources are very limited, this is a useful approach to assess the benefits from targeting compared to a random allocation of the limited resources. Moreover, in examining the relevant factors affecting access to social pension benefits, the availability of panel data allows me to minimize potential omitted variable bias and a placebo test shows that the identified factors are indeed relevant and not just driven by spurious correlations.

As explained in Chapter 2, to address limitations in targeting and coverage of social pensions, the central government introduced social pension reforms in 2007. The results of this analysis indicate that during this time period of social pension reforms the exclusion error and inclusion error reduced but both targeting errors continue to be very high. Comparing the actual allocation of social pensions to a hypothetical random allocation, the results suggest that the benefits from targeting are relatively small for the exclusion error and relevant but decreasing over time for the inclusion error. Even though the allocation of social pensions has moved towards the Below Poverty Line (BPL) card as a more observable criterion, this criterion itself is too weakly targeted towards the poor to achieve effective targeting of the elderly poor for the social pension scheme. BPL card holding is relevant for individuals from both asset poor and asset non-poor households to access social pensions and individuals who have direct connections with the local government have higher chances to receive the benefits.

The remainder of this chapter is structured as follows: Section 3.2 provides background information on the implementation of social pensions in India and summarizes existing literature in this field. Section 3.3 presents the theoretical framework by describing the targeting challenge and how social pension reforms in the Indian context are related to it. Section 3.4 describes the data and explains the methodology. In Section 3.5, I present the results from the empirical analysis before concluding in Section 3.6.

3.2 Background

As briefly stated in Chapter 2, the national Ministry of Rural Development is in charge of the social pension scheme but state governments are responsible for the implementation through panchayats (i.e. village councils) in rural areas and municipalities in urban areas as stated in the guidelines of 1995: "The [p]anchayats/[m]unicipalities will be responsible for implementing the schemes [and] are expected to play an active role in the identification of beneficiaries" (Government of India 1998, p.4). In addition to the eligibility age of 65 years as stipulated by the national government, the original guidelines stated that the "applicant must be a destitute in the sense of having little or no regular means of subsistence from his/her own sources of income or through financial support from family members or other sources" (Government of India 1998, p.7). While the central government did not provide any further instructions on how to assess destitution, if state governments had already criteria in place, they were allowed to use those. However, the national government had "the right to review these criteria and suggest appropriate revised criteria" (Government of India 1998, p.7). Several states (Punjab, Manipur, Mizoram, Meghalaya, Assam, Maharashtra and Karnataka) used their own resources to extend social pension coverage to poor women aged 60 years and older. Rajasthan even provided social pensions to poor women aged 55 years and older and to men 58 years and older (see Table 3.7 for state-specific eligibility ages). In 2011, the national government followed this trend and reduced the eligibility age to 60 years as per national guidelines (Government of India 2011).

As already sketched in the previous chapter, at the national level, the social pension reforms in India aimed at increasing the social pension amount as well as the coverage. In 2006, the central government contribution to the social pension amount was increased from 75 INR to 200 INR and the central government requested all state governments to match the central government contribution (Government of India 2006). In terms of purchasing power parity (PPP), 75 INR correspond to 6.8 international $ in 2005 and 200 INR correspond to 12.5 international $ in 2012 (World Bank 2016c). As described in more detail in Kaushal (2014), even several years after the reform, in 2011-12 many state governments do not match the central government contribution. Even if they do, the total social pension amount remains typically substantially below the Indian poverty line being on average 447 INR (ca. 40.4 international $) in rural India and 579 INR (52.4 international $) in urban India in 2004-05 and 816 INR (51.0 international $) in rural India and 1000 INR (62.4 international $) in urban India in 2011-12 (Reserve Bank of India 2013). As shown by HelpAge International in a database on social pensions, compared to other countries that have means-tested targeted social pension schemes, social pension amounts in India are very low. For instance South Africa's old-age grant is about 107 international $ and Brazil's social pension amount is about 300 international $ (HelpAge International 2015).

Further as stated above, in 2007, to increase the coverage, the central government declared that all elderly individuals whose age is 65 years or higher and live in a below poverty line household would be eligible to receive the social pension and recommended the use of BPL card to identify the elderly living in poor households (Government of India 2007). The national official policy guideline was hence to universalize social pensions among the elderly within the BPL category. However, in reality, financial allocations were insufficient to cover all elderly living in BPL card holding households (Dutta et al. 2010, p.65).

Hence, from 2004-05 to 2011-12 the targeting approach for social pensions stipulated by the central government changed - instead of instructing local government officials to select the destitute elderly as beneficiaries, since 2007, they were supposed to use a more concrete criterion, the BPL card, for targeting. Prior to 2007, the criteria for identifying “destitute” individuals were largely chosen by the state governments. While some might have used BPL card holding already then, after 2007 BPL card holding became a mandatory criterion for access to benefits from the national old-age pension scheme.

Following the national level social pension reforms, during the considered time period from 2004-05 to 2011-12 state governments also increasingly introduced BPL card holding as eligibility criterion for state level social pension schemes. In several major states the vague destitution criterion was replaced by the BPL card holding criterion (see Chapter 4 for detailed information on the state level eligibility criteria in 7 major states). Hence, the relevance of holding a BPL card to access social pensions has also increased in terms of state level regulations.

In India, the BPL card is also commonly used for access to other social protection schemes despite strong criticism of its allocation which often excludes poorer households and allows non-poor households to access benefits (Alkire & Seth 2013; Khera & Drèze 2010; Ram et al. 2009). The Ministry of Rural Development provides guidelines for the identification of “Below Poverty Line” households to the state governments. Until now, four BPL censuses have taken place in 1992, 1997, 2002 and 2011 using each a different methodology and different proxy indicators (Ram et al. 2009). Based on different surveys capturing the allocation outcomes of the first three censuses, researchers have made the targeting problems of BPL cards evident: “[N]early half of all poor households in rural India did not have a BPL card around 2005” (Drèze & Khera 2017, p.557).

Beyond the methodological issues of each BPL census, there is a more general discontent with the distribution of BPL cards. In particular, it has been criticized and empirically shown that BPL card allocation is politically influenced enabling better connected households (typically not the poor) to benefit more (Aman & Agrarwal 2014; Jhabvala & Standing 2010; Panda 2015; Ram et al. 2009).

As briefly mentioned before, previous literature on the targeting performance of social pensions in India is limited. To date, there has been no comprehensive assessment of the targeting performance of social pensions in India and the existing knowledge relies on few studies which assessed the targeting performance of BPL cards, or focused on specific states to examine the implementation of social pensions. In the case of Rajasthan, Dutta (2008) reports evidence of under-coverage, high transaction costs of the application process, and not strictly enforced eligibility criteria. Writing her paper at a time when a stronger reliance on the BPL criterion for social pensions was under consideration, she further emphasizes that using BPL cards as eligibility criterion would rather worsen than strengthen the targeting of social pensions. This is in line with Ajwad (2007) who found for Uttar Pradesh in 2004-05 that 70 percent of individuals from the poorest quintile did not possess any BPL or Antyodaya card (for the poorest families in the country), while 13 percent of the richest quintile possessed one of the two ration cards. Similarly, Ram et al. (2009, p.67) show that 40 percent of the BPL cards are possessed by non-poor households in India, and many deprived households do not hold a BPL card. Finally, Mishra & Kar (2017) show in a recently published paper that BPL card holding does not reflect asset poverty in the context of Odisha. Given the move from the destitution criterion towards the BPL card criterion, the targeting performance of social pensions in India is directly interlinked with the targeting performance of BPL cards.

Related to the targeting performance in the context of social pensions, it is important to note that filing an application for a social pension at the local administrative authorities is a requirement for sanctioning of social pensions. Based on a series of surveys focused on the evaluation of public entitlements in several states, Drèze & Khera (2014, 2017) describe the application process as very bureaucratic and slow requiring several documents as well as long waiting times.

3.3 Theoretical Framework

After briefly summarizing the theoretical literature on the targeting challenge in general, I describe the theoretical expectations on how the targeting performance and factors determining access to social pensions developed in a time period of social pension reforms in the Indian context.

3.3.1 The targeting challenge

The theoretical motivation behind targeting is clear: Allocating public resources only to those in need improves the effectiveness of poverty alleviation measures and keeps public spending low (e.g. Coady et al. 2004a). Targeting of social protection schemes gained particular importance during macroeconomic and structural adjustments when governments had to reduce public expenditures (White 2017). However, targeting itself can be very costly especially in developing countries where data availability is limited and administration weak (Besley & Kanbur 1990). Based on the various challenges that targeting is exposed to; even the strongest supporters agree that it is impossible to achieve precise targeting. Information gaps, missing data, misreporting and corruption lead to exclusion and inclusion errors. These problems tend to be even more severe in developing countries that need effective poverty alleviation most (Coady et al. 2004b). High exclusion errors and/or inclusion errors reduce the impact of any anti-poverty scheme (Slater et al. 2009). The exclusion error stands for undercoverage and the inclusion error for leakage (Coady et al. 2004a). As shown in Table 3.1 below, an individual is wrongly excluded from an anti-poverty program if she is poor and does not receive the benefits and wrongly included if she is non-poor and receives the benefits that are targeted towards the poor.

Table 3.1: Exclusion and inclusion error

	Welfare status of individual	
	Poor	Non-poor
Individual does not receive benefits from anti-poverty program	Exclusion error	Successful targeting
Individual receives benefits from anti-poverty program	Successful targeting	Inclusion error

Source: Adapted from Coady et al. (2004a, p.10).

Following Coady et al. (2004a, p.10), these two commonly used measures of mistargeting are quantified as follows. The indicator for the exclusion error is the number of poor individuals who are excluded from the program ($N_{p,o}$) divided by the number of poor individuals (N_p):

$$\text{Exclusion error} = \frac{N_{p,o}}{N_p} \tag{3.1}$$

The indicator for the inclusion error is the number of beneficiaries of the anti-poverty program who are classified as non-poor ($N_{np,i}$) divided by the number of beneficiaries (N_i):

$$\text{Inclusion error} = \frac{N_{np,i}}{N_i} \tag{3.2}$$

This analysis will shed light on how the described social pension reforms affected the targeting performance of India's social pension scheme by measuring the exclusion and the inclusion error. Whether the exclusion error or the inclusion error is more important to judge the overall targeting performance of an anti-poverty program is not obvious and a researcher's perspective evaluating the targeting performance may differ from a policy-makers perspective designing a targeted welfare scheme. Given major financial constraints for the provision of anti-poverty programs particularly in developing countries, policy-makers traditionally focused on keeping the inclusion error low by using narrowly defined eligibility criteria to keep the costs of the anti-poverty intervention low (Cornia & Stewart 1993). In this context, exclusion errors did not receive much attention because the limited financial resources implied that only some of the poor could benefit from the intervention.

In the last decades, more governments have moved towards a human rights-based approach. Based on this way of thinking, an exclusion error implies that an individual is deprived of her rights and therefore the mitigation of errors of exclusion have received much more attention by policy-makers (Drèze & Khera 2017). From a researcher's perspective, it needs to be taken into account that exclusion and inclusion errors are strongly interlinked. For instance, if a government decides to use stricter requirements for documenting poverty status to reduce the inclusion error, this comes at the risk of increasing the exclusion error as individuals from poor households would struggle to comply with the new requirements for documentation. Similarly, if a government chooses to reduce the requirements for documenting poverty status to facilitate access to social transfers for poor households, this would reduce the exclusion error but increase the inclusion error as it will be also easier for non-poor households to provide the documents. Hence, both targeting errors are important for the evaluation of the targeting performance (Coady et al. 2004a).

3.3.2 Theoretical expectations

The welfare effects of social pensions are at the maximum when elderly poor (targeted individuals) receive social pensions and elderly non-poor or individuals who are younger than the eligibility age (non-targeted individuals) do not. However, exclusion error and inclusion error exist for multiple reasons and could be particularly severe among the elderly target group. Existing literature suggests that the poorest elderly face the biggest difficulties in accessing social pensions. They are more likely to lack awareness as well as capabilities and documents required during the application process. Their transaction costs for application might also be substantially higher if they lack experience of dealing with local governments and/or if they live in remote areas (Mujahid et al. 2008). Those who are aware of the social benefits, better connected to local government bodies and capable to deal with the application procedures might be more likely to obtain access. In the following, I describe first the theoretical expectations for the targeting performance at the aggregate level and second for the role of different factors at the individual level. It is relevant to describe expectations at two different levels. The targeting performance is typically assessed at the aggregate level and factors determining access to social transfers at the individual level.

Aggregate targeting performance

With the aim to enhance the effectiveness of social pensions, in 2007 the national government issued guidelines that declared an increase in the coverage and redefined eligibility criteria by recommending the Below Poverty Line card holding as criterion for access to social pensions.

With the declaration that all elderly living in below poverty line households are eligible, the first reform increased the availability of social pensions. The substantial increase in the number of social pension beneficiaries (as documented in Chapter 1) is expected to increase the coverage of the elderly poor, and to reduce the exclusion and inclusion errors. The indicators of the targeting performance do not only improve because of the increased availability of social pensions but also because the prior extreme rationing of social pension benefits was implicitly advantageous for better informed or better connected individuals who were able to apply for social pension benefits before the resources for social pensions were exhausted. This advantage in terms of timing of the application for social pension has been recduced with the substantially increased coverage.

The effect of redefining the eligibility criteria and giving more weight to BPL card holding is rather ambiguous. On the one hand choosing one single indicator for eligibility facilitates the application procedure for applicants and the selection for local government officials (see Chapter 4). Consequently, the targeting performance could be improved i.e. coverage of the elderly poor increases and exclusion and inclusion error decrease. On the other hand, BPL cards themselves have been criticized for being weakly targeted (e.g. Alkire & Seth 2013). If the previously stipulated destitution criterion was better targeted towards the poor than BPL cards, I would expect to observe a deterioration of the targeting performance. However, if, despite of the limitations in their allocation, BPL cards were better allocated towards the poor than the previously used destitution criterion, I would expect to observe an improvement of the targeting performance. Thus, introducing BPL ration cards as eligibility criterion would only lead to an improvement of targeting of social pensions if these cards were better targeted towards the poor than the local governments' selection based on the 'old' destitution criterion. Given these theoretical expectations, the question whether the introduction of this reform improved the targeting performance can only be answered empirically. These expectations are examined in the descriptive part of the empirical analysis. Beyond the concern that BPL cards are not well targeted, the switch from the vague destitution criterion to the easily observable BPL card holding as criterion can affect the targeting performance in terms of official eligibility criteria. Whether more officially eligible individuals receive the social pension with this change, will be studied in the following chapter of this dissertation.

Access to social pensions

At the individual level, examined in the regression analysis, targeting problems directly influence who obtains access to social pensions and who does not. The theoretical expectations on the factors determining individual level access to social pensions are therefore based on the scarcely existing literature on the targeting weaknesses of social pensions in India and also influenced by research on the relevance of social capital for access to public benefits in developing countries. Given the particular difficulties in targeting prevalent in a developing country context, I expect that access to social pensions does not only depend on an individual's eligibility. For obtaining relevant information or documents during the application phase and finally receiving social pensions, contacts and embeddedness in a local network should also matter.

First, I expect that individual's eligibility determined by age and poverty status – destitution before 2007 and increasingly BPL card holding after – is positively associated with the likelihood to access social pensions. Before the reform, proxies for destitution such as the ownership of household assets or land holding might have been used to determine the destitution of the older person. After the reform, I expect to observe an increased importance of BPL card holding. This expectation is entirely based on the official documents Government of India (2007) and should be evident in the regression results if state and local governments followed the nationally modified eligibility criteria.

Second, I anticipate that direct connections to local government officials can influence the selection of beneficiaries and expedite the granting of social pensions. This concern of preferential treatment depending on political connections has been raised already for the last decades. Drèze & Sen (1989, p.107) emphasized that political influence is likely to determine the allocation of funds by local governments across the poor and the non-poor. Particularly the decentralization of the administration of anti-poverty transfers with local governments receiving greater responsibilities was accompanied by elite capture of public funds (Kochar 2008). Recently, Panda (2015) showed the relevance of political connections for accessing BPL cards in the Indian context, which reinforces the expectations that connections to local governments also play a role for other social benefits such as social pensions.

Third, I expect that membership of social organizations and participation in public meetings affect access to social pensions. Regular participation in public meetings and other social activities can play an important role in spreading awareness related to welfare schemes and I therefore expect that participating in public meetings as well as membership in social organizations can help to acquire information on social pensions.

3.4 Data and Methodology

3.4.1 The India Human Development Survey

The IHDS was conducted by the National Council of Applied Economic Research and the University of Maryland (Desai & Vanneman 2010, 2015). This nationally representative individual-level panel dataset surveyed 41,554 households (215,753 individuals) in 1503 villages and 971 urban neighborhoods across India using a stratified, multistage sampling procedure in 2004-05 and re-interviewed households in 2011-12. The survey is spread over all the states and union territories of India except Andaman & Nicobar Islands and Lakshadweep which together account for less than 0.05 percent of India's population. The IHDS includes a broad range of economic development question modules regarding demographics, health, public welfare programs, fertility, agriculture, employment, gender relations and women's status, beliefs, education, social networks, institutions, etc. at both individual and household level (Desai & Vanneman 2010, 2015). From IHDS data, I use information on social pension receipt, eligibility of the individual (age, land holding, household assets and BPL card holding), local government connection, participation in public meeting and membership in a social organization. Local government connection is a dummy variable indicating whether someone from the household, or someone close to the household is a local government official. Participating in public meetings is a dummy variable indicating whether the household has participated in a public meeting called by the village panchayat in the last year. Membership in social organizations indicates whether anybody in the household belongs to a social group such as women group, religious group, caste association and self-help group.[1] I control for working status, any permanent employment in the household, literacy, education, mass media usage, household size, number of adults living in the household, urban area, belonging to scheduled castes (SC), scheduled tribes (ST) or other backward castes (OBC), and village level development indicators. The complete list of variables and their definitions is shown in Table 3.6 in the Appendix. As IHDS is the first national panel data set covering a variety of topics related to human development and was collected before and after the major reforms in 2006 and 2007, it is the most suitable data set for the analysis of social pension targeting in India.

Apart from these factors explaining the choice of the data set, a relevant limitation is that IHDS data does not indicate whether the individual receives the social pension from the national government or from the state government[2]. This data limitation does not affect the analysis of who receives social pensions but constrains the policy implications of the results making it impossible to relate targeting errors either to the state level or to the national level social pension scheme.

In the empirical analysis, I focus on individuals in the relevant age group and exclude children and adults who are much younger than the eligibility age. Based on descriptive statistics from IHDS showing that the age-related eligibility cutoff is not strictly enforced in practice (see Figure 3.5 in the Appendix), I use a sample of individuals who are at maximum 10 years younger than the state level eligibility age for social pension (see Table 3.7 in the Appendix for state level eligibility ages). Moreover, for assessing the changes in relevant factors over time, it is essential for the regression analysis that individuals are surveyed twice. To ensure comparability between the descriptive statistics and empirical estimations, I present the entire empirical analysis for a balanced panel.

3.4.2 Methodology

The empirical analysis is divided into two parts. I first describe the methodology for analyzing the targeting performance at an aggregate level and afterwards proceed to describing the regression analysis focusing on individual level factors associated with the likelihood of obtaining social pension benefits.

1 Questionnaires and further information is available on the IHDS website: https://ihds.umd.edu/

2 In 2004-05, IHDS surveyors asked whether respondents received the National Old Age Pension Scheme. However, as respondents were unable to distinguish between the national and the state pension scheme, the question was changed, and in 2011-12, surveyors asked whether individuals received the Old Age Pension.

Analysis of targeting performance

The descriptive analysis of the targeting performance is based on the calculation of three commonly used measures for assessing the targeting performance: Coverage of targeted individuals, exclusion error and inclusion error. Based on the official objective to alleviate poverty among the elderly, targeted individuals are at least as old as the eligibility age and poor. Hence, the coverage of targeted individuals is the number of targeted individuals receiving social pensions divided by the number of targeted individuals. The exclusion error is defined as the ratio of the number of targeted individuals (i.e. at least as old as the eligibility age and poor) not receiving social pensions and the number of targeted individuals. The inclusion error is the number of non-targeted individuals (i.e. either younger than the eligibility age or non-poor or both) receiving social pensions divided by the number of beneficiaries.

To measure poverty, I focus on asset ownership. I follow Filmer & Pritchett (2001) who use an asset index to capture household's wealth in the Indian context and apply similarly to their study a principal component analysis to obtain a weighted asset index of durable assets including ownership of TV, mobile phone, bicycle, motorbike, electric fan, fridge, toilet type, floor type and water access type. This produces an asset index varying from -3.48 to 3.55 with a mean value of 0. The asset index is strongly positively correlated with consumption expenditures per capita. Following Booysen et al. (2008, p.1118) who study poverty in seven sub-Saharan African countries, I use the 40th percentile as a poverty line i.e. an individual is counted as poor if she lives in a household whose asset ownership index is lower than the 40th percentile in the asset index distribution. To take into account that living standards differ between states, rural and urban India and over time, the distribution is stratified by state, urban residence and year of data collection. Based on this definition of asset poverty, an individual is wrongly excluded if she is asset poor, older than the eligibility age and does not receive a social pension. An individual is wrongly included if she is asset non-poor or younger than the eligibility age (or both) and receives a social pension.

Focusing on asset poverty instead of consumption poverty is preferable here since I evaluate the targeting performance retrospectively and cannot rule out behavioral reactions to social pension receipt that would directly affect consumption expenditure. Since a certain share of elderly in the data set is already receiving social pensions, I cannot simply count them as wrongly included if their consumption expenditures are just above the poverty line. Their consumption expenditures might have been pushed above the poverty line by the social pension receipt and in the absence of the social pension receipt their consumption expenditures would have been lower than the poverty line and hence the individual would have been considered as correctly included. A potential approach would be to simply subtract the received social pension amount from the consumption expenditures to approximate the value of the consumption expenditures if the individual had not received the social pension. However, this subtraction would be based on two misleading assumptions. First, I would need to assume that either social pension income is entirely pooled with other household income or entirely consumed by the older person. Second, simply subtracting the received social pension amount would neglect any behavioral reactions taking place in response to the social pension receipt. For instance the social pension income might allow elderly to reduce their labor market participation which would lower their consumption expenditures but also reduce their daily consumption need. Both assumptions seem to be problematic. Ownership of durable assets in contrast is a more stable indicator of financial well being of a household that is unlikely to be affected by social pension receipt as the benefits are very low ranging from 200 INR to 1000 INR and primarily spent for consumption and not for durable assets (e.g. HelpAge International 2009).[3]

Another advantage of using assets instead of consumption expenditures is of practical relevance for the design of welfare schemes. Compared to income or consumption expenditures which cannot be easily measured (or even recalled) in a developing country context, survey data on durable assets is in general of higher quality and could be also easily used for future identification of the poor if the government decides to replace BPL card holding as relevant indicator.

Regardless of whether the measures are based on consumption expenditure or asset ownership, they suffer from the limitation that by being measured at the household level they neglect intra-household inequalities. Elderly might be disadvantaged in their households and hence in the empirical analysis older poor people living in non-poor households may be wrongly considered as non-poor despite of their individual need for social pension benefits.

I compare the targeting errors of social pensions to the targeting errors of a hypothetical random allocation of social pension benefits. This is helpful to understand how the existing targeting approach performs compared to a much cheaper alternative – the random allocation of social pensions. The difference between the targeting error under random allocation and the actual targeting error indicates the benefits of targeting social pensions

3 I have carried out the same analysis previously with consumption expenditures and the results are overall very similar.

towards the poor instead of distributing social pensions randomly to individuals.

This hypothetical random allocation of social pension benefits also allows me to address the concern that the sheer expansion of social pension coverage influences the size of the targeting errors by taking into account the social pension coverage in both years.[4] Theoretically, even if social pensions were allocated randomly, expanding the coverage would imply that the exclusion error would decrease while the inclusion error would increase. However, this is not the only factor playing a role here. In addition, from 2004-05 to 2011-12 the number of targeted individuals increased since the eligibility age was reduced in most states. The increase in the number of targeted individuals affects both errors in the opposite direction. Ceteris paribus, the increase in the number of targeted individuals would lead to an increase in the exclusion error and a decrease in the inclusion error. Given these two opposing forces, the development of the targeting errors under random allocation remains an empirical question.

Analysis of factors related to access to social pensions

To understand which factors affect access to social pensions, I estimate a linear probability model with the baseline specification presented below. For all specifications, the dependent variable is social pension receipt and the variables of interest reflect eligibility for social pension receipt (age, household assets, land holding and BPL card) and social capital (local government connection, public meeting and social organization). I exploit the panel data structure of the data to estimate regressions with individual fixed effects. This approach minimizes the omitted variable bias related to unobserved time-invariant individual characteristics that cross-sectional regressions are suffering from. All control variables as described above are included. To account for changes over time, I include a dummy variable for the later time period 2011-12 (*After*) which also addresses the concern that the results might be partially driven by the expansion of social pension coverage from 2004-05 to 2011-12. I further use interaction terms between the time dummy and variables of interest to assess how factors changed over time. Finally, I am interested in understanding whether the factors of interest, namely eligibility and indicators of social capital, play a different role for asset poor and asset non-poor households and how these factors changed over time. To test this empirically, I employ triple interactions of the time dummy, the variables of interest and a dummy for being poor in terms of asset ownership.

4 I thank Stefan Klonner for having pointed this out.

$$\begin{aligned}\text{Social pension}_{it} = \beta_0 + \beta_1\text{Age}_{it} + \beta_2\text{Assets}_{it} + \beta_3\text{Land}_{it} + \beta_4\text{BPL card}_{it} \\ + \beta_5\text{Local government connection}_{it} + \beta_6\text{Public meeting}_i t + \beta_7\text{Social organization}_{it} \\ + \beta_8\text{After}_t + \mathbf{X'_{it}}\gamma + a_i + u_{it} \quad (3.3)\end{aligned}$$

In line with the objectives of this analysis, the linear probability model is particularly suitable for the estimation of marginal effects in fixed-effects regression models (Angrist & Pischke 2009; Wooldridge 2003) and for examining changes over time with interaction terms (Ai & Norton 2003). I present robust standard errors that are adjusted for the heteroscedasticity in the estimation of linear probability model (Wooldridge 2003).

The empirical analysis of individual-level factors related to social pension access suffers from two limitations that should be taken into account before proceeding to the interpretation of the results:

First, people could lie about social pension receipt and BPL card holding if they were aware of not being eligible for receiving social pensions or holding a BPL card. Since the IHDS surveyors clearly explained the research purpose of the survey, it is rather unlikely that individuals had any motivation to lie about these aspects in front of a surveyor visiting their households. However, a minor social desirability bias cannot be ruled out.

Second, while local government connection and BPL card holding are incorporated in the regression analysis as two independent variables predicting social pension receipt, in reality holding a BPL card is endogenous to having a a local government connection. The factors influencing BPL card holding are certainly important for the effectiveness of several welfare schemes in India and need to be examined to obtain a deeper understanding of the targeting performance. An in-depth analysis of the factors determining BPL card allocation needs to be conducted for a representative sample of all Indian households and not just for a sample of the elderly. This goes beyond the focus of this chapter and is therefore left for future research.

3.5 Results

3.5.1 Descriptive Statistics

The sample used for the analysis is only restricted by the age of the individuals and therefore includes beneficiaries and non-beneficiaries of social pensions. It consists of all elderly who are at maximum 10 years below the eligibility age and surveyed twice by IHDS (balanced panel). The summary statistics are shown in Table 3.2 separately for 2004-05 and 2011-12.[5] The share of elderly receiving a social pension increased from 4.2 percent in 2004-05 to 17.8 percent in 2011-12. Concerning the independent variables of interest indicating eligibility for social pensions, the figures indicate that the average age for the individuals in the sample has increased from 61.1 years to 68.0 years, corresponding to the time between the two survey rounds, and the share of elderly living in households that hold BPL cards increased from 33.7 percent to 40.9 percent.

Ownership of assets increased from 12.9 to 15.5 assets on average out of 30 assets while the size of land holding declined from 2.4 acres to 2.0 acres on average. These are both indicators of wealth that states might have used to assess the poverty status of social pension applicants prior to the national social pension reforms. Since the destitution criterion provided by the national government lacked any further specifications, state governments were able to identify beneficiaries based on criteria in place.

Concerning the independent variables of interest indicating social capital in different forms, the share of elderly living in households that are directly connected with the local government officials has increased substantially from 11.7 percent to 28.7 percent. Participation in public meetings stayed stable (30.9 percent to 31.3 percent) and membership in social organizations increased from 37.0 percent to 40.2 percent.

All covariates developed over time as expected. Watching TV has become more common (from 47.8 percent to 55.7 percent), reading newspaper stayed stable (from 26.1 percent to 25.0 percent) and education levels of the elderly in the balanced sample of analysis stayed unsurprisingly at the same level with 3.1 years of education on average in 2004-05 and 2011-12. Directly related to the increased age of the individuals in the sample of analysis, the share of individuals working (defined as having worked at least 240 hours in the last

5 For simplicity, I use the term elderly even though the sample includes individuals who are at maximum 10 years below the local eligibility age for social pensions.

year) declined from 56.5 percent in 2004-05 to 34.4 percent in 2011-12.[6] This reduction seems to be primarily driven by the higher age of individuals in the sample. Moreover, the share of elderly living in households in which at least one person has a permanent job, slightly increased from 15.0 percent to 17.8 percent. I also control for village level variables indicating development in the village (electrification rate), collaboration between villagers (village collaboration rate) and absence of conflicts (peaceful village rate). All these three indicators measured at the village level have improved over time with a higher share of households having electricity (from 77.0 percent to 88.2 percent), a higher share of households reporting that families help each other to solve local problems (from 58.4 percent to 73.2 percent) and a slightly higher share of households reporting that people get well along with each other (from 53.3 percent to 59.7 percent)

The variable asset poor in the bottom of Table 3.2 indicates whether an individual lives in an asset poor household based on the methodology described before. Since I set the poverty line at the 40th percentile of the full IHDS sample, by construction the shares of elderly living in poor households in 2004-05 and 2011-12 are also close to 40 percent.

6 This also confirms that I cannot rule out the existence of behavioral responses to the social pension receipt as described in the methodology section reasoning the focus on asset poverty instead of consumption poverty.

Table 3.2: Summary statistics

	2005				2012			
	mean	sd	min	max	mean	sd	min	max
Social pension	0.042	0.20	0	1	0.178	0.38	0	1
Age	61.089	7.77	45	100	68.009	8.46	45	99
BPL card	0.337	0.47	0	1	0.409	0.49	0	1
Household assets	12.890	6.25	0	30	15.472	6.30	0	30
Land holding	2.440	5.97	0	200	2.024	6.86	0	400
Local government connection	0.117	0.32	0	1	0.287	0.45	0	1
Public meeting	0.309	0.46	0	1	0.313	0.46	0	1
Social organization	0.370	0.48	0	1	0.402	0.49	0	1
Watching TV	0.478	0.50	0	1	0.557	0.50	0	1
Reading newspaper	0.261	0.44	0	1	0.250	0.43	0	1
Literate	0.431	0.50	0	1	0.426	0.49	0	1
Education	3.152	4.37	0	15	3.095	4.34	0	15
Highest adult education	8.415	5.06	0	15	8.626	5.10	0	15
Working	0.565	0.50	0	1	0.344	0.48	0	1
Permanent job in household	0.150	0.36	0	1	0.178	0.38	0	1
Electrification rate	0.770	0.29	0	1	0.882	0.20	0	1
Households collaborate rate	0.584	0.32	0	1	0.732	0.25	0	1
Peaceful village rate	0.533	0.36	0	1	0.597	0.34	0	1
Head of household	0.493	0.50	0	1	0.507	0.50	0	1
Widow	0.234	0.42	0	1	0.354	0.48	0	1
Household size	6.133	3.25	1	38	5.449	2.94	1	30
Number of adults	3.779	1.65	1	18	3.692	1.64	1	18
Urban	0.279	0.45	0	1	0.303	0.46	0	1
Other backward castes	0.408	0.49	0	1	0.412	0.49	0	1
Scheduled castes	0.176	0.38	0	1	0.179	0.38	0	1
Scheduled tribes	0.064	0.24	0	1	0.066	0.25	0	1
Female	0.536	0.50	0	1	0.536	0.50	0	1
Hindu	0.824	0.38	0	1	0.829	0.38	0	1
Muslim	0.095	0.29	0	1	0.096	0.29	0	1
Asset poor	0.393	0.49	0	1	0.411	0.49	0	1
Observations	15185				15185			

The sample is restricted to individuals at maximum 10 years younger than the eligibility age.
For the definitions of all variables see the Appendix. The variables social pension, age, education, working, head of household, widow and female are measured at the individual level; the other variables are measured at at the household level except for village collaboration rate, peaceful village rate and electrification rate which are measured at the level of the primary sampling unit (village in rural areas and neighborhoods in urban areas).
Source: Author's illustration based on IHDS I for 2004-05 and IHDS II for 2011-12.

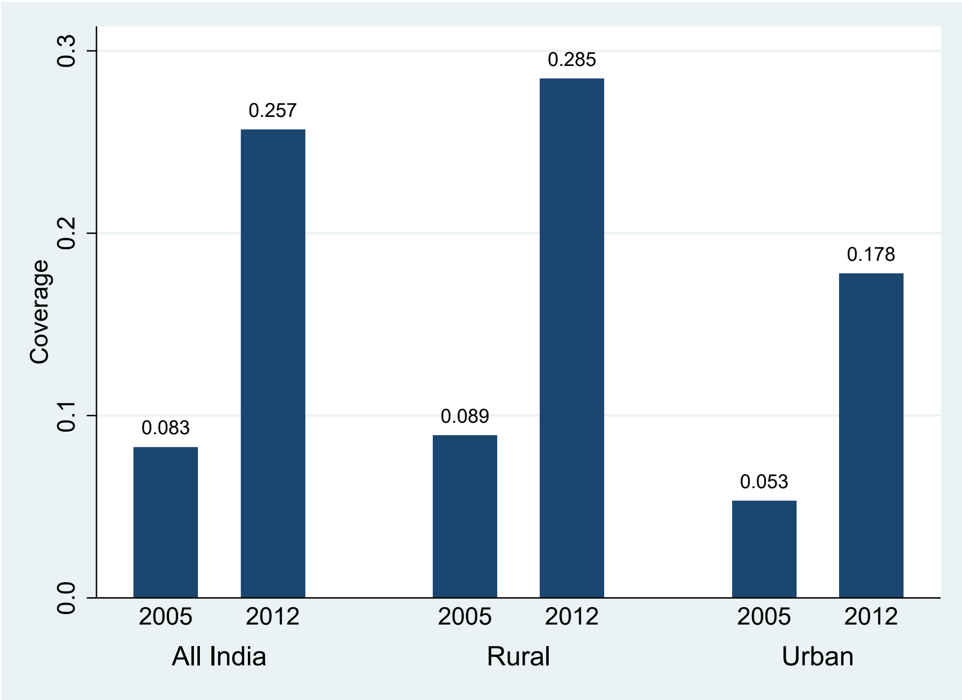
The summary statistics are in line with my theoretical expectation that the elderly poor might face greater difficulties in accessing social pensions because they lack capabilities such as literacy or basic education levels required during the application process. As shown above, the education levels of elderly are in general quite low with on average 3.1 years of schooling and a literacy rate of 42.9 percent. However these mean values mask important heterogeneities. Elderly poor (i.e. living in an asset poor household) have on average only 1.6 years of completed education and a literacy rate of only 28.3 percent, making interactions with the bureaucracy much more difficult to handle (Desai & Vanneman 2010, 2015).

Difficulties with the application procedures in particular with long waiting times or travel to administrative institutions may be particularly problematic for elderly with limited mobility. In 2004-05 only 7.4 percent of the individuals have difficulties with activities of daily living (ADL) and 3.5 percent have difficulties with walking. However, directly related to the increased age in 2011-12, these shares rise to 30.1 percent and 22.3 percent respectively. These statistics indicate that a substantial share of elderly in the sample is constrained in their mobility in 2011-12. The constrained mobility is particularly problematic for elderly living in poor households that typically lack vehicles or financial resources to pay for transportation required during the application process (Desai & Vanneman 2010, 2015).

Similar to the summary statistics that showed a larger share of the elderly receiving social pension benefits in 2011-12, Figure 3.1 shows that the social pension coverage of the elderly poor improved substantially over time. In the sample of analysis, the share of elderly poor receiving social pensions increased from 8 percent to 26 percent overall, the improvement was similar for rural and urban areas but rural areas already had a higher coverage of the elderly poor in 2004-05.[7]

7 This development is driven by the fact that the government expanded the social pension coverage, however to some extent it is also simply driven by the fact that all the elderly individuals in sample of analysis have become seven years older in between the two survey rounds.

Figure 3.1: Coverage of targeted individuals



Targeted individuals are at least as old as the eligibility age and poor. Poverty is measured by asset ownership. Figures account for sampling weights.
Source: Author's illustration based on IHDS I for 2004-05 and IHDS II for 2011-12.

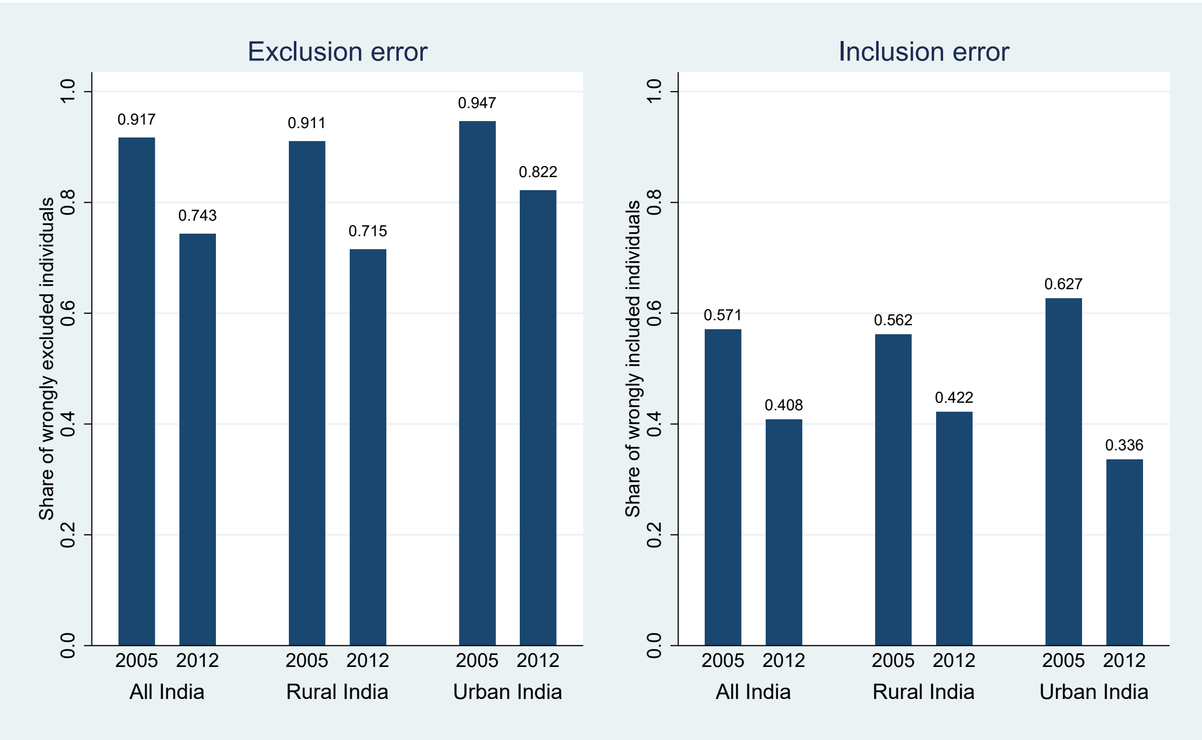
Regarding the targeting errors, the descriptive results in Figure 3.2 and Figure 3.3 show that even though both targeting errors have been reduced over time, the targeting errors after more than 15 years of implementing the scheme continue to be very high with large shares of individuals being wrongly excluded and large shares of individuals being wrongly included. There has been a considerable reduction of the exclusion error by 17 percentage points from 2004-05 to 2011-12, but still 74 percent of the elderly poor do not receive the social pension benefit. The inclusion error was also reduced from 57 percent to 41 percent but two-fifths of the beneficiaries are still wrongly included in 2011-12, i.e. they are either non-poor or too young or both. The general pattern is similar for rural and urban India. Overall, both errors continue to be very high.

Since these targeting errors appear to be very high, I proceed to assess how the targeting of social pensions in India performs in comparison to a hypothetical random allocation of social pension benefits. As illustrated in the second part of Figure 3.2, in 2004-05 the real exclusion error was only 4 percentage points lower than the exclusion error under random allocation and this difference increased only to 8 percentage points in 2011-12.

For the inclusion error, I observe a different development. In contrast to the small but positive change in terms of exclusion error, the benefits of targeting decreased in terms of the inclusion error, from 26 percentage points in 2004-05 to 19 percentage points in 2011-12 (at national level). Overall, these results show that despite of the social pension reforms, the benefits from targeting compared to the random allocation seem to be very small. This raises the question whether the benefits from targeting of social pensions are larger than the costs of targeting. This will be an important question for future research requiring data on the costs of targeting in the Indian context.

The weak performance of the actual targeting of social pensions compared to the hypothetical random allocation of social pensions might be also related to the weak targeting performance of BPL cards in particular in the second time period. The correlation between being asset poor and holding a BPL card is only 0.21.[8] The dissonance between BPL card holding and poverty has been shown in several previous studies as described above. The relevance of BPL card holding for access to social pensions at the individual level will now be examined in the following section.

Figure 3.2: Targeting errors



Development of exclusion error and inclusion error from 2004-05 to 2011-12.

Source: Author's illustration based on IHDS I for 2004-05 and IHDS II for 2011-12.

8 The examination of the targeting performance for rural and urban India masks important differences between the states in terms of targeting performance. I therefore also show the development of the targeting errors for India's major states in Figure 3.6 in the Appendix.

Figure 3.3: Benefits from targeting

Comparing targeting errors from random allocation to targeting errors from actual allocation.
Source: Author's illustration based on IHDS I for 2004-05 and IHDS II for 2011-12.

3.5.2 Regression results

Below I present the results from the linear probability model estimations in different specifications. All regression specifications include all control variables, time fixed effects and individual fixed effects. Table 3.3 shows the regression results introducing the social capital variables separately and in the last specification jointly. The coefficients are very close to each other in size. I describe in the following the results from the last specification.

Ceteris paribus, the coefficient of the dummy for the period after the reform estimates the change in the likelihood of receiving a social pension in year 2011-12 relative to year 2004-05. Obtaining access to social pension in 2011-12 is 10.6 percentage points more likely than in 2004-05. This difference is significant at the 1 percent level and seems to be primarily attributable to the expansion of the coverage. Age is as expected positively associated with access to social pensions (significant at the 5 percent level) and holding a BPL card increases the likelihood to receive a social pension by 6.7 percentage points (significant at the 1 percent level). Household assets are weakly negatively associated with access to social pensions (significant at the 10 percent level).

Table 3.3: Panel analysis of access to social pensions

	(1)	(2)	(3)	(4)
After the reforms	0.106***	0.109***	0.109***	0.106***
	(0.010)	(0.010)	(0.010)	(0.010)
Age	0.003**	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
BPL card	0.067***	0.068***	0.067***	0.067***
	(0.008)	(0.008)	(0.008)	(0.008)
Household assets	-0.002*	-0.002*	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Land holding	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Local government connection	0.019**			0.019**
	(0.008)			(0.009)
Public meeting		0.004		0.001
		(0.007)		(0.008)
Social organization			-0.006	-0.006
			(0.007)	(0.007)
Ind. fixed effects	Yes	Yes	Yes	Yes
Observations	30370	30370	30370	30370
Number of id	15185	15185	15185	15185
Avg. predicted value	0.10	0.10	0.10	0.10
Share of predicted values in [0;1]	0.85	0.85	0.85	0.85
Adj. R-aquared	0.13	0.13	0.13	0.13

Standard errors in parentheses

The dependent variable is social pension receipt. Regressions account for sampling weights. Cluster-robust standard errors are shown in parentheses. All described control variables are included.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Regarding the social capital variables, the panel regression results support the theoretical expectation on the relevance of connections to the local government for access to social pension benefits. If an individual lives in a household that has direct connections to the local government, the likelihood to receive social pensions increases by 1.9 percentage points (significant at the 5 percent level). Participation in public meetings and membership in social organizations are not significantly associated with social pension receipt.

Given the average predicted value of social pension receipt being 10 percent, the size of the coefficients is also economically significant.

These results provide a first impression of the relevant factors but do not indicate how these factors have changed over time in response to the described reforms in 2006–07. Table 3.4 presents the marginal effects for each time period resulting from the regression including all variables of interest and their interaction terms as well as all control variables and individual fixed effects. To test whether the relevance of the variables of interest namely BPL card holding, local government connection, participation in public meetings and membership in social organizations changed from 2004-05 to 2011–12, I include interaction terms of the dummy variable for 2011-12 and these variables of interest in the regression. The presented estimates always show the relevant correlation between the variable of interest and social pension receipt for the period before the reforms in 2004-05 and the period after the reforms in 2011-12. As can be derived from the full regression table in the appendix, the estimate for the variable of interest before the reforms simply corresponds to the coefficient of the variable. The correlation of the variable of interest with social pension receipt after the reform corresponds to the linear combination of the coefficients of the variable of interest and the variable of interest interacted with the dummy for the period after the reforms. Hence, the first row of Table 3.4 indicates the correlation between the variable of interest and social pension receipt in the time period before the reform, the second row shows the correlation between the variable of interest and the social pension receipt in the time period after the reform. The bottom row indicates whether the correlation before is significantly different from the correlation after the reforms.

In line with the changed national eligibility guidelines, BPL card holding becomes substantially more important for access to social pensions after the reform. In 2011–2012, living in a BPL card holding household increases the likelihood of receiving a social pension by 15.3 percentage points indicating that the centrally reformed eligibility criterion was implemented (at least to some extent) by the state governments in panchayats and municipalities. At the time of the 2011-12 survey, the BPL card had become the most important determinant of access to social pensions, is significant at the 1 percent level (Table 3.4)

In contrast to that, as mentioned above, prior to the reform, local government officials were requested to select individuals for the national social pension scheme based on the destitution criterion. The results somewhat surprisingly show that if an individual lives in a household that holds a BPL card in 2004-05, his or her likelihood of gaining access to social pensions is reduced by 3.0 percentage points (significant at the 1 percent level). One potential explanation for the negative coefficient in the time period before the reform could be that individuals who have a BPL card are able to access other anti-poverty schemes (such as subsidized food or public works program) and are therefore considered as less destitute by local government officials than those who do not even have a BPL card. Especially in the context of rationed provision of social pensions prior to 2007, it could be the case that benefiting from other schemes already through the BPL card makes accessing social pension benefits less likely during the time period when the vague destitution criterion was described by the national government as eligibility criterion.

My expectation for the relevance of connections with the local government is supported by the empirical analysis. As shown in Table 3.4 direct connections with local government officials gained importance over time. In 2004-05 the relevant coefficient is insignificant but the estimation of the marginal effects for 2011-12 indicates that living in a household that has a connection to the local government is associated with a 2.1 percent points higher likelihood of receiving social pensions (significant at the 10 percent level). This increase over time can be related to progressing decentralization processes and the local government being increasingly important for the allocation of social safety nets and public services.

Table 3.4: Access to social pensions - marginal effects before and after the reform

	BPL	Local government connection	Public meeting	Social organization
Before	-0.030***	0.010	-0.004	-0.000
	(0.004)	(0.482)	(0.717)	(0.978)
After	0.153***	0.021*	0.005	-0.014
	(0.000)	(0.062)	(0.653)	(0.104)
P-value of difference	0.000	0.569	0.551	0.228

For readability, I present marginal effects for the variables of interest before and after the reforms. The marginal effect for the period after the reform is derived from the linear combination of the coefficients presented in the full regression output in Table 3.8 in the Appendix. P-values are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

These results potentially mask heterogeneity in the factors playing a role for elderly from poor and non-poor households. To examine the heterogeneity between these two groups for access to social pension benefits before and after the reform, I include triple interaction terms of the time dummy for 2012, the variables of interest and the dummy for living in an asset poor household. The variable asset poor is equal to 1 if the household's asset ownership is lower than the asset poverty line as explained above.

As shown in Table 3.5, before the reforms, the negative and significant coefficient of BPL card holding that I observe for the full sample is driven by the individuals living in asset non-poor households. I do not observe the negative association between BPL card holding and social pension for individuals living in asset poor households. After the reform, BPL card holding is relevant for individuals living in asset poor and asset non-poor households. For individuals living in asset poor households, BPL card holding is associated with a 13.1 percentage points' higher likelihood of receiving social pensions (significant at the 1 percent level). For individuals from asset non-poor households it is similarly associated with a 14.2 percentage points' higher likelihood of receiving social pensions (significant at the 1 percent level). This result strongly suggests that non-poor individuals exploit the unwarranted possession of BPL cards to obtain social pension benefits. Further, the effect of local government connections on social pension receipt seems to be primarily driven by individuals living in asset non-poor households. The effect of 2.5 percentage points is significant at the 5 percent level for individuals from non-poor households and insignificant for individuals from poor households. The remaining social capital variables on participation in public meetings and membership in social organizations remain insignificant for either of the two groups.

Table 3.5: Heterogeneous marginal effects for asset poor and asset non-poor individuals

Period	Variable	Asset poor	Asset non-poor	P-value of difference
Before	BPL card	-0.009	-0.032**	0.256
After	BPL card	0.131***	0.142***	0.572
Before	Local government connection	0.008	0.006	0.907
After	Local government connection	0.018	0.025**	0.782
Before	Public meeting	0.007	-0.013	0.260
After	Public meeting	0.020	-0.002	0.322
Before	Social organization	-0.005	-0.0016	0.938
After	Social organization	-0.011	-0.008	0.889

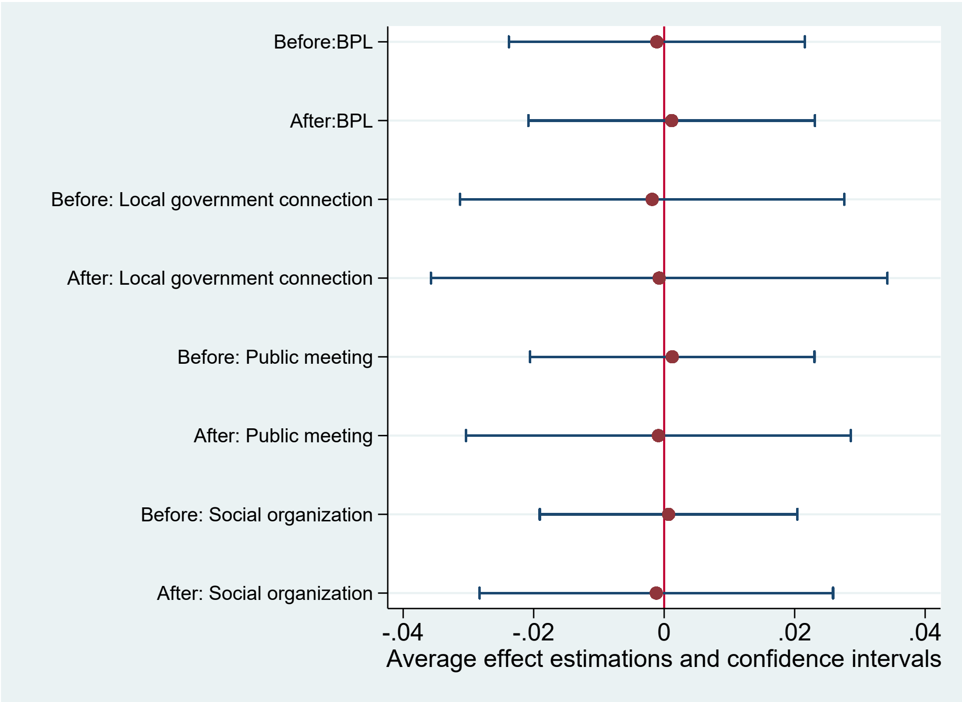
For readability, I present marginal effects. The marginal effects for the period after the reform and for asset-poor households are derived from the relevant linear combinations of the coefficients presented in the full regression output in Table 3.9 in the Appendix. P-values are shown in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.5.3 Robustness

The increased coverage could lead to a simultaneity bias if both the dependent variable and the independent variables of interest increased independently driven by some unobservable factors. I am particularly concerned by the relatively strong increase observed for the dependent variable social pension receipt increasing from 4.2 percent to 17.8 percent and the independent variables BPL card holding increasing from 33.7 percent to 40.9 percent and local government connection increasing from 11.7 percent to 28.7 percent. Spurious correlations could be the only reason for observing that BPL card holding and connections to local government officials have become more important for access to social pension benefits from 2004-05 to 2011-12 as described in the previous section.

Similar to the assessment of the benefits of targeting described before, I address this concern by conducting a placebo test (Figure 3.4). In 100 simulations, I randomly assign social pension receipt in both time periods to the individuals in the sample of analysis to mimic the coverage expansion that took place from 2004-05 to 2011-12. In this random allocation, I take into account the number of beneficiaries in 2004-05, in 2011-12 and how many individuals received social pensions in both rounds. I also account for the fact that in the Indian social pension system, individuals who start to receive a social pension in one period typically continue receiving it in the next period independent of changes in their poverty status as subsequent checks of the poverty status do not seem to take place. Given this random allocation, I run the above regressions again in 100 simulations and use random pension receipt as dependent variable. Under random allocation, the positive and significant effects of political connections and BPL card holding, which I observed for the period after the reforms in all specifications, completely disappear. Thus the placebo test confirms that the previously found relationships between these two variables of interest and the dependent variable are indeed relevant and not only caused by a spurious correlation between the left hand side variable and the right hand side variables. The results of the placebo test are visualized below showing the average of the estimated coefficients of the variables of interest and their 95 percent confidence intervals.

Figure 3.4: Placebo test



Source: Author's illustration and estimation based on IHDS I for 2004-05 and IHDS II for 2011-12.

3.6 Conclusion

This chapter aimed to examine the targeting performance of social pensions in India and to answer the question of who receives social pension benefits. The descriptive statistics show that from 2004-05 to 2011-12, a time period encompassing important national social pension reforms, the targeting of social pensions improved but both targeting errors continue to be very high. The exclusion error decreased substantially from 92 percent to 74 percent and the inclusion error from 57 percent to 41 percent. This development indicates an improvement of the targeting performance but also shows that a major share of resources continues to be absorbed by non-targeted individuals who are either non-poor or younger than the retirement age (or both). The reduction of the exclusion error seems to be primarily achieved through the expanded coverage allowing elderly to apply any time and increasing their chances to obtain access to social pension benefits. Nevertheless, the persistently high targeting errors indicate that social pension reforms in the past have not been successful in facilitating access for the majority of elderly poor. Particularly, the low benefits of targeting apparent when comparing the targeting errors under random allocation to actual targeting errors imply that there is urgent need to reconsider the targeting of social pension benefits in India due to the obvious difficulties in identifying elderly poor. For the ongoing debate on targeting versus universalizing social pension benefits for all elderly, future research that achieves to compare the costs of targeting to the benefits of targeting will be particularly informative.

As intended by the reforms, the results show that holding a BPL ration card has become the primary determinant of access to social pensions. However, this result holds also for non-poor individuals who exploit the unwarranted possession of a BPL ration card to obtain social pension benefits. The results further indicate that in the time period after the reforms, connections to local government officials indeed facilitate access to social pension benefits. This result in combination with the insight that weakly targeted BPL cards enable non-poor individuals to access social pension benefits makes evident how challenging targeting has been since the introduction of targeted anti-poverty schemes and continues to be despite the described reform efforts in the Indian context.

Although with the reforms of the national social pension scheme in 2007 the allocation of social pensions has shifted towards a more observable criterion, the BPL card, this criterion itself is too weakly implemented to achieve effective targeting of the poor. This indicates the deeply-rooted targeting problem of ration cards in India. Hence, using the allocation of ration cards as a tool to allocate benefits of a social protection scheme implies a transfer of the targeting weaknesses of ration cards to the social pension scheme.

Universalization of social pensions to provide basic income support to all elderly and potentially greater support to the most vulnerable elderly appears to be the most desirable option (see e.g. Drèze & Khera 2017, p.557). However, universalization of social pensions in the near future does not seem to be a financially feasible option because of India's very limited tax base. Only 1 percent of the Indian population pays taxes (Ghatak 2017).

The results directly support the existing literature which recommends a reform of the allocation of BPL cards and suggests alternative targeting approaches for social pensions such as the use of clear exclusion criteria that at least prevent clearly non-poor elderly from accessing social benefits targeted at the poor and facilitate access to social pensions for the elderly poor. The simplification of criteria would help to increase the awareness of entitlements, facilitate application procedures and make monitoring of beneficiary selection easier. Different to previously used scores summing up different dimensions of economic well-being, these inclusion and exclusion criteria would be easily verifiable and even directly observable within a village or an urban neighborhood. Several of the suggested criteria are also captured in secondary data sources (such as census data) and would allow the detection of "gross cheating" for instance at the panchayat level (Khera

& Drèze 2010, p.61). The 2011 Socio Economic Caste Census with its focus on relatively simple and verifiable inclusion and exclusion criteria was already an important step in the suggested direction and is now already used for some other schemes (Alkire & Seth 2013).

This analysis is not without limitations and some important open questions remain for future research: First, even though the improved coverage and the increased relevance of BPL card holding for access to social pensions correspond to the objectives of the social pension reforms by the central government in 2007, I am unable to clearly attribute these changes to the efforts of the central government. IHDS lacks information on whether individuals receive benefits from the national scheme or from the state scheme and the observed improvements might have also been influenced by the efforts of state governments to expand or better target social pension benefits. Analyzing the factors behind the differential targeting performance of state schemes and national schemes running in parallel in several states can yield relevant insights to improve the targeting performance of social pensions (or other schemes). Second, taking intra-household inequality into consideration, the targeting performance of India's social pension scheme should be ideally evaluated at the individual level. Even in relatively well-off households, due to intra-household inequality, elderly poor might suffer from deprivation. Understanding how individual level targeting could work in the context of developing countries would be an important milestone for future research and policy advice.

Given the described data limitations, this chapter provides a relevant groundwork for future research on the targeting performance of social pensions. Ideally, using primary data collection tailored to evaluate the targeting performance, more concrete conclusions can be drawn and policy implications made.

Finally, the effectiveness of social pensions in the Indian context might be additionally constrained by the inadequately low amounts in several states. Future research that exploits the variation in social pension amounts jointly with the variation in the targeting performance across Indian states would contribute to understanding to what extent the effectiveness in reducing old-age poverty does not only vary with the targeting performance but also with the adequacy of the social pension amount.

Appendix

Table 3.6: List of variables

Variable	Definition
Social pension	Dummy variable equal to 1 if individual receives social pension, 0 otherwise
After	Dummy variable equal to 1 if data was collected in 2011-12 after the national social pension reforms, 0 otherwise
BPL card	Dummy variable equal to 1 if individual is entitled to benefits through the ration card (either BPL or Antyodaya), 0 otherwise
Age	Age of the individual
Household assets	Asset index for number of assets owned by household from 0 to 30
Land holding	Land holding in acres
Local government connection	Dummy variable equal to 1 if somebody from the household or close to the household is a local government official, 0 otherwise
Public meeting	Dummy variable equal to 1 if individual belongs to a household that has participated in public meeting last year and 0 otherwise
Social organization	Dummy variable equal to 1 if anybody in the household is a member of a social organization, 0 otherwise
Watching TV	Dummy variable equal to 1 if individual belongs to a household watching TV regularly, 0 otherwise
Literate	Dummy variable equal to 1 if individual can read and write, 0 otherwise
Education	Years of schooling completed
Highest adult education	Years of schooling completed of the most educated household member
Working	Dummy variable equal to 1 if individual works more than 240 hours per year, 0 otherwise
Permanent job in household	Dummy variable equal to 1 if anybody in the household has a permanent job, 0 otherwise
Collaboration rate	Share of households in the village/block reporting that families collaborate to solve local problems

Peaceful village rate	Share of households in the village/block reporting that people in the village/block in general get well along with each other
Share of electrified households	Share of electrified households in village or block
Head of household	Dummy variable equal to 1 if individual is head of household, 0 otherwise
Widow	Dummy variable equal to 1 if individual is widowed, 0 otherwise
Household size	Number of individuals living in the household
Number of adults	Number of adults living in the household
Urban	Dummy variable equal to 1 if individual lives in a household in urban areas, 0 otherwise
Scheduled tribes	Dummy variable equal to 1 if individual lives in a household belonging to scheduled tribes, 0 otherwise
Scheduled castes	Dummy variable equal to 1 if individual lives in a household belonging to scheduled castes, 0 otherwise
Other backward castes	Dummy variable equal to 1 if individual lives in a household belonging to other backward castes, 0 otherwise
Female	Dummy variable equal to 1 if individual is female, 0 otherwise
Hindu	Dummy variable equal to 1 if individual lives in a Hindu household, 0 otherwise
Muslim	Dummy variable equal to 1 if individual lives in a Muslim household, 0 otherwise
Asset poor	Dummy variable equal to 1 if individual belongs to a household whose asset ownership is lower than the 40th percentile in the asset index distribution, 0 otherwise

Source: Author's illustration based on IHDS I for 2004-05 and IHDS II for 2011-12.

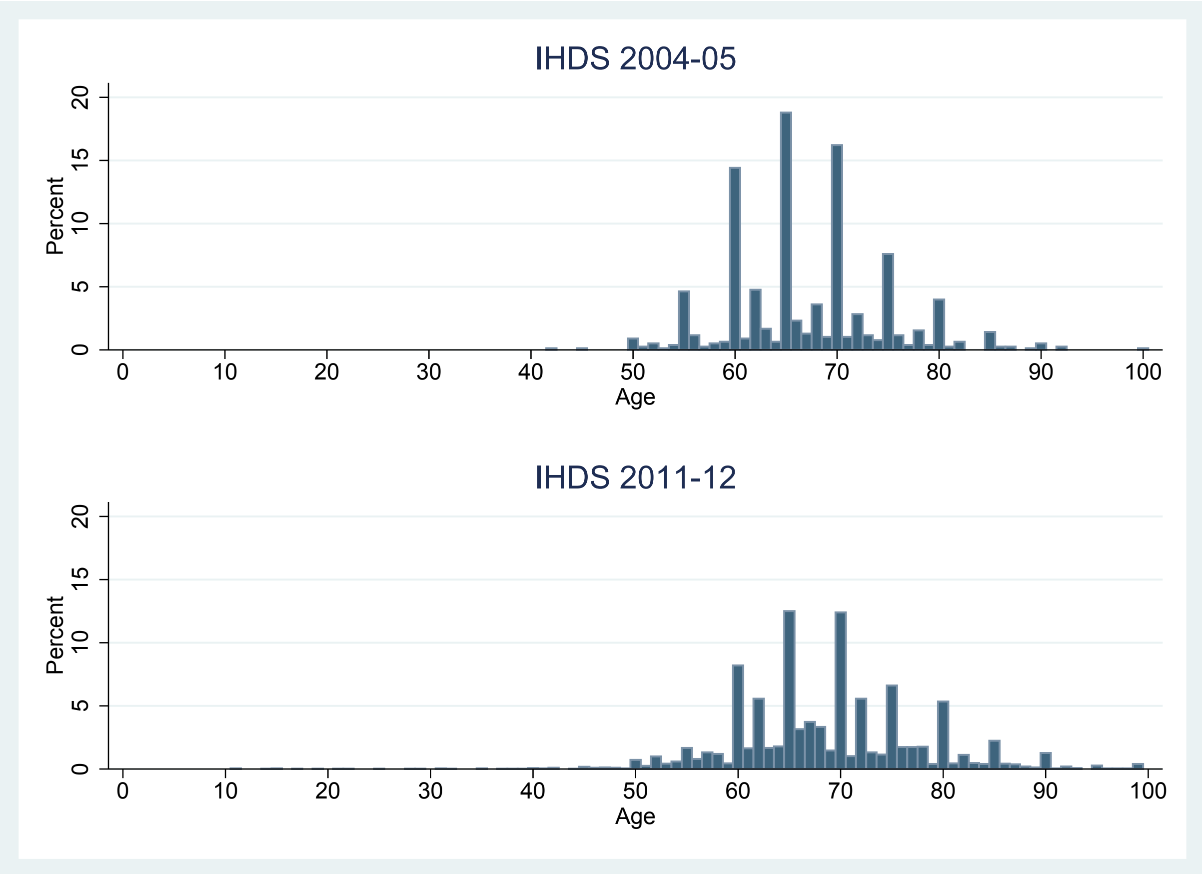
Table 3.7: State wise eligibility ages for social pensions

State	2004-05	2011-12
Jammu and Kashmir	65	60
Himachal Pradesh	65	60
Punjab	60 (f), 65 (m)	60
Chandigarh	65	60
Uttarakhand	65	60
Haryana	65	60
Delhi	60	60
Rajasthan	55 (f), 58 (m)	55 (f), 58 (m)
Uttar Pradesh	65	60
Bihar	60	60
Sikkim	65	60
Arunachal Pradesh	60	60
Nagaland	65	60
Manipur	60 (f), 65 (m)	60
Mizoram	60 (f), 65 (m)	60
Tripura	65	60
Meghalaya	60 (f), 65 (m)	60
Assam	60 (f), 65 (m)	60
West Bengal	65	60
Jharkhand	65	60
Odisha	65	60
Chattisgarh	65	60
Madhya Pradesh	65	60
Gujarat	60	60
Daman & Diu	60	60
D & N Haveli	65	60
Maharashtra	60 (f), 65 (m)	60
Andhra Pradesh	65	60
Karnataka	60 (f), 65 (m)	60
Goa	60	60
Lakshadweep	60	60
Kerala	65	60
Tamil Nadu	65	60
Pondicherry	60	60
Andaman Islands	60	60

Notes: m: male, f: female

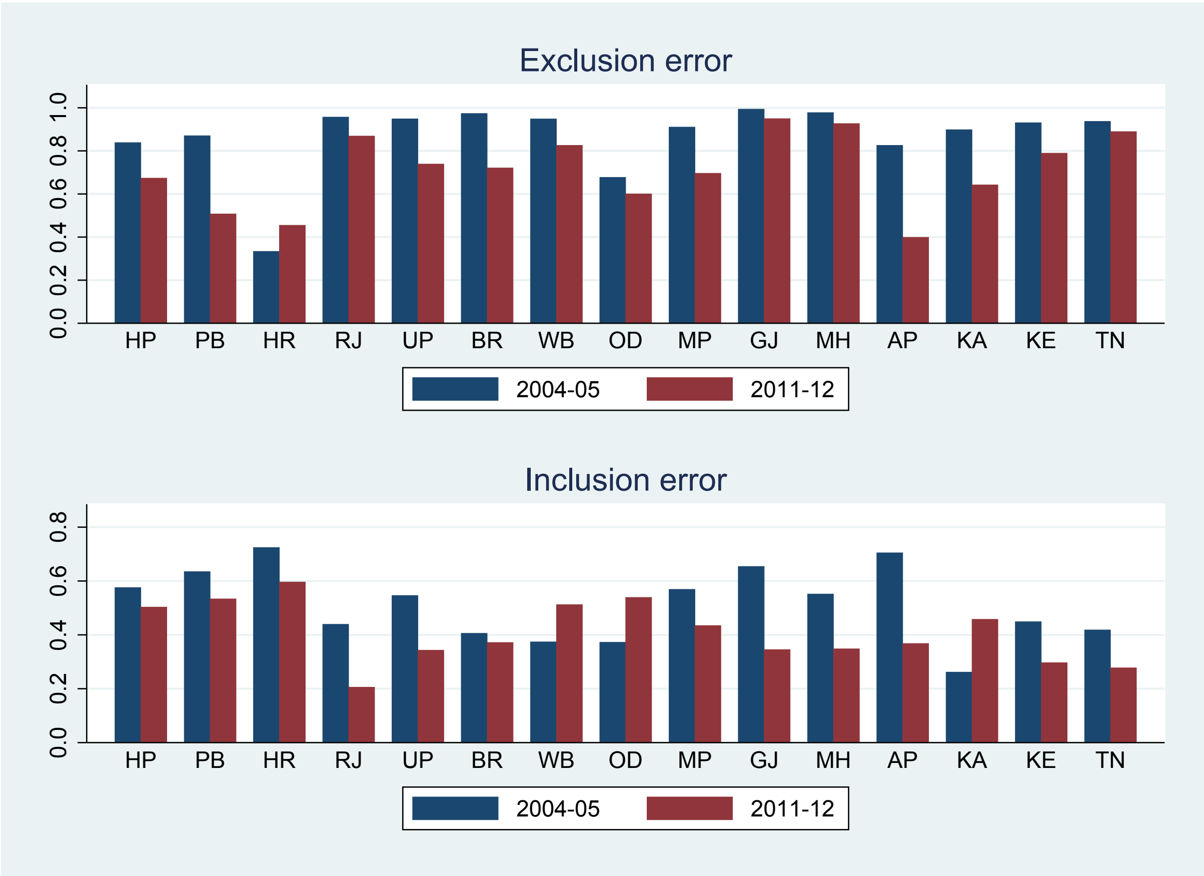
Source: Author's illustration based on Kaushal (2014) and Government of India (2011).

Figure 3.5: Age distributions of social pension beneficiaries



Notes: As shown in this figure for the full IHDS sample, people seem to report their age more precisely in 2011-12. Potentially this is related to the better quality of IHDS data in 2011-2012 as communicated by the IHDS team or it could be related to the fact that people from later cohorts are able to indicate their age more precisely than people from earlier cohorts.
Source: Author's illustration based on IHDS I for 2004-05 and IHDS II for 2011-12.

Figure 3.6: Targeting errors in India's major states



All states with at least 500 observations per round in the sample. Figures account for sampling weights. Source: Author's illustration based on IHDS I for 2004-05 and IHDS II for 2011-12.

Table 3.8: How did the factors change over time?

	(1)
	Social pension
BPL card	-0.030**
	(-2.87)
After X BPL card	0.182***
	(15.45)
Local government connection	0.010
	(0.70)
After X local government connection	0.010
	(0.57)
Public meeting	-0.004
	(-0.36)
After X public meeting	0.008
	(0.60)
Social organization	-0.000
	(-0.03)
After X social organization	-0.014
	(-1.21)
Ind. fixed effects	Yes
Observations	30370
Number of id	15185
Avg. predicted value	0.10
Share of predicted values in [0;1]	0.90
Adj. R-squared	0.17

t statistics in parentheses

The dependent variable is social pension receipt. Regressions account for sampling weights. Cluster-robust standard errors are shown in parentheses. All control variables are included.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.9: Heterogeneity analysis for asset poor and asset non-poor individuals

	(1)
BPL card	-0.032*
	(-2.55)
After × BPL card	0.175***
	(10.88)
BPL card × asset poor	0.023
	(1.14)
After × BPL card × asset poor	-0.035
	(-1.27)
Local government connection	0.006
	(0.44)
After × local government connection	0.018
	(0.98)
Local government connection × asset poor	0.002
	(0.05)
After the reforms × local government connection × asset poor	-0.008
	(-0.21)
Public meeting	-0.013
	(-1.19)
After × public meeting	0.011
	(0.74)
Public meeting × asset poor	0.020
	(0.89)
After × public meeting × asset poor	0.002
	(0.06)
Social organization	-0.002
	(-0.17)
After × social organization	-0.006
	(-0.47)
Social organization × asset poor	-0.004
	(-0.19)
After × social organization × asset poor	0.001
	(0.04)
Ind. fixed effects	Yes
Observations	30370
Number of id	15185
Avg. predicted value	0.10
Share of predicted values in [0;1]	0.89
Adj. R-aquared	0.17

t statistics in parentheses

The dependent variable is social pension receipt. Regressions account for sampling weights. Cluster-robust standard errors are shown in parentheses. All control variables are included.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4

Do More Transparent Eligibility Rules Improve Public Program Targeting?

4.1 Introduction

The previous chapter focused on examining whether social pensions reach the elderly poor. Another relevant question is whether those who are in charge of selecting beneficiaries follow the official eligibility criteria. This chapter therefore examines whether targeting errors measured according to the official criteria (instead of using a general poverty criterion) can be reduced if eligibility criteria are formulated in a more transparent way.[1]

As wide-spread corruption, local capture, and clientelism prevent the effective delivery of basic social services to the intended beneficiaries in many developing countries, policy interventions raising the level of transparency have been widely shown to improve poor people's access to these services (Björkman & Svensson 2009; Francken et al. 2009; Olken 2007; Peisakhin 2012; Peisakhin & Pinto 2010; Reinikka & Svensson 2004, 2005, 2011). So far, these studies focus on service delivery processes. At the most basic level, however, transparency starts with the definition of eligibility criteria. These criteria are transparent if they are clear and easy to verify. Owing to the lack of reliable income data, the identification of poverty needs to rely on proxy means tests. How to design these proxy means tests and which criteria should be included remains a subject of ongoing debate to which we wish to contribute in this paper.

India's old-age social pension reforms in the late 2000s provide us with the opportunity to directly test the relationship between changes in eligibility criteria and targeting performance. Social pensions are non-contributory pensions, i.e., direct government cash transfers to the elderly. Reforms of eligibility criteria were implemented both for national

1 This chapter is based on a paper that is co-authored with Katharina Michaelowa, Sitakanta Panda and Sourabh B. Paul and currently under review for publication in a journal.

and state pension schemes. At the national level, for instance, the central government replaced the previously vague poverty-related criterion "destitution" (without any operational definition) by the requirement to belong to a "Below Poverty Line" (BPL)-card holding household. This BPL card is also used for numerous other benefits such as food or fuel subsidies and health care. Whether a household is in possession of a BPL card or not is an easily observable criterion and leaves no room for interpretation.

Note that whether the BPL card itself is correctly targeted to the poor is a different question that has been discussed elsewhere in the literature (Alkire & Seth 2013; Hirway 2003; Jain 2004; Panda 2015; Government of India et al. 2009; Sundaram & Tendulkar 2003), and that we cannot cover here. However, our study will have implications for access to anti-poverty schemes in general, and thus also be indirectly relevant for future reforms of eligibility for BPL cards.

Theoretically, one would expect a trade-off between the specificity and detail of eligibility criteria, and their transparency, whereby the former ensures that the criteria correctly characterize the most vulnerable beneficiaries, while the latter ensures that they are implementable in practice. In this study, we assess the relevance of the latter. If we find a sizable effect of transparency on the correct implementation of service delivery regulations, then the above trade-off needs to be taken seriously in policy reforms. Attempts to refine criteria so as to best capture the intended target population should consider the negative side-effects such detailed definitions may have on actually reaching the poor. At the same time, simplifying existing criteria may provide a resource-effective means to channel the benefits of social security programs to the neediest individuals.

To assess the effect of transparent eligibility rules on actual implementation, we will proceed in the following way: First, we develop a new indicator of eligibility-criteria-related transparency combining the insights of previous studies (Niehaus et al. 2013; Khera & Drèze 2010). Second, we define targeting error strictly along the lines of the regulations in official government documents, rather than on the basis of externally imposed poverty measures. This requires a detailed assessment of the rules applicable at national and sub-national level and their change over time. Third, we consider a tolerance band around the eligibility cut-off points. When criteria are intransparent, i.e., either vague or very complex, it may be difficult for a local government official to exactly define the correct target group. But as long as the selected beneficiaries are close to those intended, this may still be better than using easy but broad criteria in the first place. Our computation and application of a tolerance band takes this consideration into account and leads to a more conservative assessment of the effect of transparent, i.e., usually more simplified and verifiable eligibility conditions.

Beyond the detailed administrative data collected from national and sub-national documents and web search, we use two rounds of the India Human Development Survey (IHDS) to examine the relationship between the change in eligibility criteria and the targeting error over time. We find statistically and economically significant results that are robust to variations in the specification of the transparency measure and various robustness checks.

4.2 Literature and Theory

This chapter contributes directly to the literature on the role of transparency for the targeting performance of anti-poverty schemes. While prior studies examined primarily the relevance of transparent delivery mechanisms (Björkman & Svensson 2009; Francken et al. 2009; Olken 2007; Peisakhin 2012; Peisakhin & Pinto 2010; Reinikka & Svensson 2004, 2005, 2011). In contrast, we focus on the transparency of eligibility criteria that may be more easily amenable to reform. Most closely related to our study, Niehaus et al. (2013) analyze how a proxy means test should be designed if the "implementing agent is corruptible" (p. 206). The authors focus on complexity through the number of conditions. They show both theoretically and empirically that using more conditions to define eligibility for an anti-poverty scheme is likely to deteriorate the targeting performance. Intuitively their findings indicate that rule breaking becomes more likely if there are more rules that a local government official needs to follow for the allocation of benefits. In a context of widespread corruption, the officials can make use of the ambiguity created by the higher complexity to allocate benefits in line with their own preferences. While the accuracy of a poverty indicator often increases with the number of specific conditions, these conditions may simply not be enforceable.

As corruption is an important concern in large parts of the developing world (and beyond), these findings are highly relevant for the implementation of welfare schemes. Other important concerns in developing countries are the lack of information and the lack of government capacity (UNCDF & UNDP 2012; UNDP 2016; World Bank 2004, 2016b,a). They may reinforce the above-mentioned implementation problems. For instance, when poor people do not know the eligibility criteria, they cannot claim their rights and hold corrupt agents responsible. For corrupt government officials themselves, lack of information or capacity may provide a good excuse in case they are caught while transgressing the rules. Furthermore, even if officials are not corrupt, lack of capacity and of relevant information may create a situation in which complex eligibility criteria cannot be enforced. Asri et al. (2020) show that this may be the case for social pension allocation in Bangladesh, where the lack of relevant information, notably on the characteristics of applicants, forces local government officials to select beneficiaries among those people they are personally acquainted with. This shows that the considerations in Niehaus et al. (2013) are very broadly applicable in developing country contexts, even beyond the context the authors themselves had in mind.

However, using the simple count of eligibility criteria as the measure of complexity is a rough simplification. Individual conditions may themselves differ in their level of complexity, i.e., there may be several sub-conditions, and the individual criteria may be more or less difficult to assess and verify.

Already in the mid 1990s, Baker & Grosh (1995) underscore that the verifiability of eligibility criteria is extremely important for the implementation of all kinds of public anti-poverty programs in developing countries where data on income are imprecise. In their work on the identification of BPL card holders, Khera & Drèze (2010) also focus on verifiability. In line with Niehaus et al.'s findings, they show the importance of using eligibility criteria that are easy to follow. But rather than to reduce the number of criteria, they suggest replacing the existing complex approach by easily verifiable inclusion and exclusion criteria which allow individuals to indicate their eligibility based on statements such as "I am eligible because I am landless" or "I am not eligible because I own a car" (p. 55). Khera & Drèze (2010) argue that this simplification will also help to facilitate participatory monitoring and to prevent fraud.

In our study, we will integrate the different aspects of complexity based on the number of criteria and their verifiability into a combined transparency indicator, while simultaneously showing the results for each of its components. In line with the authors cited above, we expect that increasing the transparency of eligibility criteria positively affects both the demand and supply sides of social pension targeting. As already illustrated in the above examples, transparency improvements influence the behavior of local government officials in charge of selecting beneficiaries (supply side) and local citizens applying for social benefits (demand side). Overall, the theoretically expected advantages are as follows:

On the supply side, through the increase in transparency, the local government officials face increased costs of preferential treatment as the likelihood of being detected is higher and therefore targeting errors are expected to be reduced. Moreover, using more transparent eligibility criteria reduces the administrative burden of selecting beneficiaries and the likelihood of human error. The use of more transparent eligibility criteria also reduces the administrative costs of social protection schemes and thereby allows that, at least in theory, these limited resources can be used as transfers to the poor.

On the demand side, increasing the transparency of eligibility criteria facilitates the application for the eligible elderly individuals. Fewer and less complex conditions simplify the application process and make the outcome of the application more predictable. Given that the applicant submits all required documents, the chances of receiving the benefits are higher compared to a situation with less transparent criteria and higher discretionary power for the local government official. Transparency of eligibility criteria moreover facilitates that people are aware of their entitlements and helps individuals to scrutinize the selection of beneficiaries in public meetings improving their influence in the beneficiary selection.[2]

Testing the effect of increased transparency of eligibility criteria in the context of social pensions in India might be a rather hard case. While the context of widespread corruption and lack of information and government capacity is certainly given in India, focusing on social pensions may make it relatively difficult to detect the effect of any change in eligibility criteria. This is because the elderly themselves are often highly constrained through physical weaknesses preventing their participation in public life and through illiteracy and lack of access to modern communication – so constrained that they may not be able to understand and/or may not be properly informed even about highly transparent criteria (unless they receive external support by family members or NGOs). This may reduce the working of the demand channel. If our estimates indicate that increasing the transparency of eligibility criteria considerably reduces targeting errors for social pensions, the effect may thus be even stronger for other welfare schemes, where the demand side is less constrained in terms of public participation, access to information and mobility.

4.3 Background on Social Pension Reforms

As already mentioned in Chapter 3, in India, social pension schemes exist at the state and national level, whereby the pensions provided by the state governments typically complement the amounts provided under the national scheme and/or widen the group of beneficiaries. The national scheme called Indira Gandhi National Old Age Pensions Scheme (IGNOAPS) was introduced in 1995 with a central government contribution of

2 In the Indian context, public meetings are supposed to be used for scrutinizing the list of beneficiaries for several anti-poverty schemes including old-age social pensions (see e.g. Besley et al. (2005)).

75 INR per person per month. Unlike social pensions in other developing countries like Nepal, Bolivia or South Africa that are paid out to all individuals above a certain age, for budgetary reasons, social pensions in India are targeted only towards the poor considering that this is the population for which support provides the greatest welfare benefits (Palacios & Sluchynsky 2006). The Ministry of Rural Development is in charge of the social pension scheme but the state governments are responsible for the implementation through gram panchayats (village councils) and municipalities. The 1998 guidelines of the National Social Assistance Programme (NSAP) state that panchayats and municipalities are responsible for the implementation of the schemes and that they shall be actively involved in the identification of beneficiaries (Government of India 1998, p.4). Panchayats and municipalities represent the smallest local governance unit in rural and urban India respectively.

IGNOAPS initially targeted elderly persons who should be 65 years or older and destitute, defined as “having little or no regular means of subsistence from his/her own sources of income or through financial support from family members or other sources” (Government of India 1998, p.7). At the same time, there was a cap on the number of beneficiaries that effectively limited the number of the destitute to 50% of the elderly with consumption expenditures below the Tendulkar poverty line (Rajan 2001, p.613). While this implicitly shifted the eligibility threshold to the median of the distribution of monthly per capita household consumption expenditure of the elderly poor (Rajan 2001, p. 613), those who did and did not belong to this group was unobservable in practice, and the vagueness of the ‘destitution’ criterion left ample discretionary power to local officials. In 2007, the previously used destitution criterion was replaced by the much more easily observable requirement that beneficiaries should live in households that hold a BPL card. In addition, minimum age was reduced to 60 years.

Regarding the complementary state pensions, we also observe several reforms of eligibility criteria. In most cases, the reforms at state level also reduced the complexity of eligibility criteria and thereby increased their transparency. For instance, in Uttar Pradesh, eligibility for the state social pension scheme was originally based on land holding in rural areas and individual income in urban areas, while after the reforms, it was purely based on BPL card holding. Other states such as Himachal Pradesh, Haryana, Odisha and Karnataka now rely largely on household income to determine the eligibility for their state-run old-age pension schemes. In yet other states such as Madhya Pradesh, state-run programs simply follow the IGNOAPS criteria. Finally, there are a few states such as West Bengal that fully abstain from running their own state-level programs. For the latter, the reform of IGNOAPS directly defines the overall change in transparency of the relevant eligibility criteria in the state.

While there is a general tendency towards the use of more easily verifiable criteria, the number of criteria increased in many states, which may reduce transparency. In any case, the above discussion shows that considerable variety regarding the transparency of eligibility criteria remains between states. This is mainly true for state-run schemes, but even the criteria for IGNOAPS are not always exactly identical across states. Based on a large number of government reports and internet sources, we compiled the exact information for the period before and after the reform for seven states. This information is presented in Appendix 4.A.

4.4 Data and Methodology

4.4.1 Generation of the data set

To test the hypothesis that transparent criteria improve targeting, we examine the likelihood of individual-level mistargeting depending on the transparency of the relevant eligibility criteria and on a number of controls. To implement this analysis, we combine two data sets with information on (i) individuals, households and communities, and (ii) administrative regulations at the state level. Unfortunately, detailed information on specific eligibility criteria and their change over time could not be compiled for all states, so that the analysis is effectively restricted to the states of Haryana, Himachal Pradesh, Karnataka, Madhya Pradesh, Odisha, West Bengal and Uttar Pradesh (see Appendix 4.A). For the individual- and community level data we rely on two waves of the India Human Development Survey (IHDS) that were conducted by the National Council of Applied Economic Research (NCAER) and the University of Maryland (Desai & Vanneman 2010, 2015) in 2004-05 and 2011-12, i.e., before and after the relevant reforms.

As described in the previous chapter, the IHDS is a nationally representative individual-level survey including a broad range of modules regarding demographics, health, public welfare programs, fertility, agriculture, employment, gender relations and women's status, beliefs, education, social networks, institutions, etc. related to individuals, households and communities. The survey covers 41,554 households in 2004-05 and 42,152 households in 2011-12 in 1503 villages and 971 urban neighborhoods across India. Sampling was based on a stratified, multistage procedure in 2004-05 (IHDS-I) and households were re-interviewed in 2011-12 (IHDS-II) (Desai & Vanneman 2010, 2015).

Given our focus on old-age pensions, in both rounds we exclude all individuals who are younger than the state specific eligibility age.[3] Finally, our dependent variable capturing the likelihood of targeting error at the individual level can only be identified for individuals in seven states for which sufficient information is available on state-level pension schemes, i.e., the seven states listed above. As a consequence, for our analysis the sample consists of 5,015 elderly surveyed in 2004-05 and 7,399 elderly surveyed in 2011-12, i.e., a total of 12,414 observations. In principle, the data allow us to create a balanced panel over the two rounds, so that individual fixed effects can be used to control for unobservable heterogeneity among the elderly. However, given that the age of those covered in the first period is already high, we lose a high number of them before the second round. The sample for the panel regression would thus not be representative for all the elderly anymore. For this reason, we focus on a pooled cross section from 2004-05 and 2011-12 in the main part of the regression analysis, and exploit the panel aspect of the data only in our robustness checks.

We combine the IHDS data with state-level administrative data on the specific social pension schemes drawn from a large number of government websites and reports.[4] As a complement to quantitative data, we also collected qualitative information through interviews with policy makers, ministerial officials, social activists and scholars specialized in social pensions for elderly. The information drawn from these interviews primarily refers to the administrative processes and was used for checking the collected administrative information. The interviews will not be analyzed directly in this study, but they provide important background information that helps in the construction of the main explanatory variable and interpretation of empirical results. We provide a list of interviews in Appendix 4.D.

3 The complete age distribution of social pension beneficiaries is presented in Appendix 4.B.

4 The data source for each variable is presented in Appendix 4.C.

4.4.2 Operationalization

Dependent variable

As we intend to measure a possible improvement in targeting, a natural choice for the dependent variable seems to be the targeting error. This error can refer both to unjustified exclusion or unjustified inclusion. Given that the correct application of the threshold still leaves many poor and deserving elderly uncovered, exclusion errors tend to be regarded as the primary concern in the Indian context. This was revealed in many of our interviews. In addition, IHDS data show that the prevalence of inclusion errors is much smaller. In fact, due to very limited social pension coverage, the number of wrongly included individuals, particularly in the 2004-05 survey, is so limited that credible statistical inference appears problematic, which is why we focus on exclusion errors in this study.

While exclusion error is generally defined as the share of eligible individuals who are excluded from social pension benefits (see Coady et al. 2004a), the dependent variable in our regressions is measured at the individual level. This excludes the computation of population shares. Instead, we simply create an indicator variable that takes the value of one if a person is 'wrongly excluded', and zero otherwise.[5]

As mentioned earlier, in contrast to the previous literature (e.g. Asri 2019), we do not impose any external normative assessment of what is 'wrong'. Rather, we consider the official criteria that public officials are supposed to follow, and try to match them as closely as possible with our data. Since the criteria vary across states and over time, a person with the same characteristics could be wrongly excluded in one place (or one point of time), and rightly excluded in another. Along with the age criterion, we hence need to consider a number of variables in this context, related to consumption expenditure, income, BPL, land holding, and/or residential status. The destitution criterion relevant primarily for the early implementation of IGNOAPS (and some state-level social pension schemes) is measured by per-capita consumption (net of social pension receipts) below the median consumption of the elderly poor, whereby poverty is defined based on the Tendulkar poverty line (separately for rural and urban areas), and median consumption of the elderly is approximated by the median of consumption expenditures (net of old-age pensions) of the household in which they live. This procedure to assess destitution corresponds to the official process used to compute the number of pensions allocated to each state (Rajan 2001, p.613).

5 It should be noted that the average for 'wrongly excluded' in our sample does not correspond to the standard measure of exclusion error either. This is because our dataset does not only include eligible individuals, but also some non-eligible elderly (as long as they are in the eligible age group).

Respondents to the IHDS do not distinguish between different social pension schemes and simply report whether or not they receive a social pension.[6] Qualifying for any existing scheme, should, in principle, lead to social pension receipt. When eligibility criteria differ between IGNOAPS and the relevant state scheme, anyone who fulfills the criteria of either of the schemes but does not receive a pension, is therefore considered as wrongly excluded.

In addition to the indicator variable for wrong exclusion, we construct a second dependent variable that is more lenient regarding minor errors. Using this alternative variable guarantees that econometric results will not be driven by only a minor divergence from official cut-off points for any of the eligibility criteria.

In principle, if local government officials were strongly committed to applying government criteria and relatively well informed, vague or complex criteria might just introduce such minor errors. Officials may not be able to assess the exact information, but still get things right at least roughly, for instance if they have to define operational proxies themselves, or if the beneficiaries cannot provide clear answers to some of many different criteria. As long as the selection of beneficiaries remains close to the target, the eligibility criteria used may still be preferable to more transparent, but less accurate ones.

Our alternative dependent variable takes such concerns into account by introducing a tolerance band around the exact thresholds of all eligibility criteria. Only if a person is clearly eligible, i.e., beyond the tolerance band for all criteria, and still not included among the beneficiaries, this person is considered as wrongly excluded according to this indicator with band.

Since methodologically, it is not possible to create a statistical error band around some arbitrary number, we instead construct a 95% confidence band around the cut-offs using the sampling distribution of the estimator of the corresponding percentile of the distribution. As most of the underlying variables are continuous, the computational procedure is straightforward. For the BPL criterion, however, we need to first reconstruct the underlying distribution of asset ownership and other socio-economic characteristics of the household. We do so by estimating a probit model to obtain the probability of holding a BPL card. The explanatory variables of this model are derived from the 13-item census questionnaire used for the 2002 BPL assessment (Ministry of Rural Development 2002). We then compute the 95% confidence interval around the mean prediction for those individuals who effectively possess a BPL card. The cut-offs for the errors with tolerance band

6 Based on this experience, NCAER adjusted the initially more specific formulation to a general one in the second round of the IHDS.

then jointly constitute the limits of the confidence interval for BPL card holding itself. For a detailed explanation of the construction of the cut-off points including tolerance bands, see Appendix 4.E.

Explanatory variables and other covariates

Our explanatory variables describe the transparency of eligibility criteria. As the computation of corresponding transparency indicators necessarily includes some subjective judgments regarding both the information included and the method of aggregation, we propose alternative indicators here that we describe in detail below and in Appendix 4.F. Making use of the detailed administrative information collected at national and state level for both periods under review (see Appendix 4.A), we develop three complementary state and time specific transparency scores. In general, the transparency score increases if eligibility criteria are fewer in number, easier to verify and less complex to implement.

For all three indicators, we first classify eligibility criteria into four main categories, namely destitution, income, land holding, and BPL card holding. In some cases, there are also additional other criteria or sub-criteria. Furthermore, there are obviously age-related criteria. The latter are relevant for the assessment of mistargeting, but we can ignore them for our transparency indicators, as their existence (as opposed to their value) is uniform across states and over time. Following Niehaus et al. (2013), our first indicator (Transparency A) simply counts the different eligibility criteria officially relevant for any specific pension scheme at a given point in time. We slightly refine this measure by also considering sub-criteria. The idea is that the sheer number of these criteria and sub-criteria matters, because any addition of conditions renders the selection process more difficult to understand (i.e. increases opacity). The transparency score is then computed by subtracting the number of relevant conditions from their empirical maximum (= 4). We finally add +1 to avoid zero numbers (for details, see Appendix 4.F).

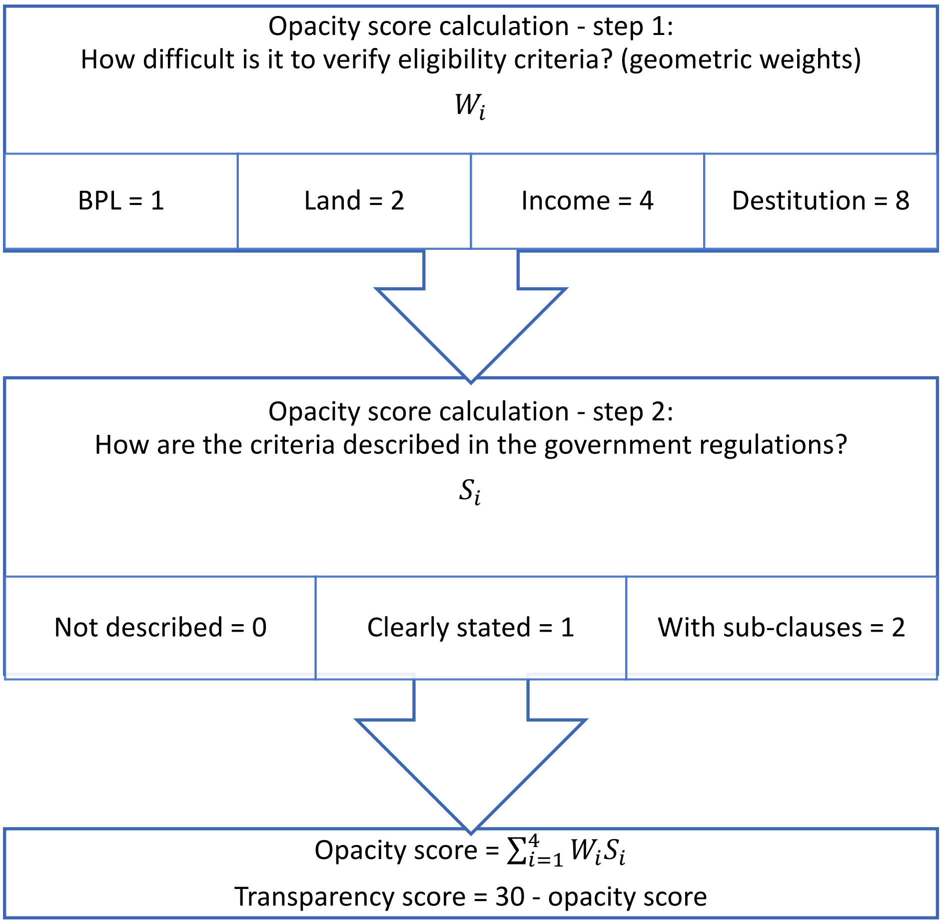
However, not all criteria are equally difficult to assess, and this may be even more relevant for transparency than the number of criteria itself. Building on Khera & Drèze (2010), we hence suggest an additional indicator (Transparency B) that considers how easily verifiable the criteria are. To construct this indicator, we assign geometric weights to each of the four categories of criteria mentioned above, increasing with the difficulty of verification (opacity). Based on our insights from our qualitative interviews, we classify BPL card holding as least difficult to verify (1 point), land holding as second-least difficult to verify (2 points), income as second-most difficult to verify (4 points) and destitution as most difficult to verify (8 points). We aggregate the numbers to a transparency score by subtracting the highest value for any criterion used in a specific pension scheme from the empirical maximum value across all observations (=8), and again add +1 to avoid an overall score of zero (for details, see Appendix 4.F).

Finally, we compute a more sophisticated version of the transparency measure (Transparency C), which combines both aspects within a single indicator (see Figure 4.1). This indicator assigns higher scores to state-level regulations that use fewer eligibility criteria and eligibility criteria that are more easily verifiable. To compute this indicator, we proceed in three steps. The first two steps generate an opacity score which we convert into a transparency score in the third step. Figure 4.1 below visualizes the calculation step by step.

We first focus on the difficulty to verify eligibility criteria and apply the same geometric weights as for Transparency B. We denote the verifiability weight of criterion i by $W_i,\ i \in \{BPL, land, income, destitute\}$. In the second step, we consider how clearly the criterion is described in the government regulations. Again in terms of opacity, we assign 0 points when the criterion is not stated, 1 point if the criterion is clearly stated and 2 points if the criterion is stated with sub-clauses. Let S_i be the opacity score of criterion i. The overall opacity score is the weighted sum $\sum_{i=1}^{4} W_i S_i$. If a state specifies all four types of eligibility criteria with maximum level of opacity, the weighted sum is $2\sum_{i=1}^{4} W_i = 30$. Finally, to obtain the transparency score C, we subtract the opacity score from the empirical maximum value (29), and again add +1, i.e.,

$$Transparency\ C = 30 - \sum_{i=1}^{4} W_i S_i.$$

Figure 4.1: Coding of transparency measure C



Source: Authors' illustration.

We further consider a number of covariates to control for confounding factors. In this context one important factor may be pension coverage, which often changes simultaneously with the introduction of new eligibility criteria. Indeed without an appropriate control for the change in coverage, any change in exclusion error that we might attribute to the influence of transparency, may actually reflect the effect of a change in the number of pensions relative to the number of eligible elderly. As a higher number of pensions was allocated in the second period, at a given number of eligible individuals, the probability of being wrongly excluded should decline, even if pensions were allocated randomly. As the increase in the number of pensions varies across states, the simple inclusion of a period dummy will not suffice to control for this. Since it is highly plausible that the number of pensions made available by each state is correlated with the transparency of the eligibility criteria (e.g. because a state that cares for the elderly poor will try to improve both, coverage and transparency), without a control for coverage, our estimator may be biased, and the effect of transparency itself may be much less pronounced than our initial regression outcomes would suggest.

At the same time, the number of eligible individuals rises between the two periods, and again this increase is not uniform across states. The effect is exactly opposite to the above since this leads to a reduction of available pensions relative to eligible individuals, and should hence increase exclusion error even if pensions were allocated randomly. Again, these design features of the pension system are plausibly determined together with other changes in the criteria, and hence cannot be considered as independent from the transparency variable.

Since this is an important concern, we will also go beyond a simple linear control variable and suggest additional non-linear specifications to deal with this problem in our robustness tests.

Apart from coverage, our data allow us to control for a large number of other possible confounders. However, some caution is necessary when selecting the control variables. Given that our dependent variables is based on thresholds, the construction of which involves a number of possibly relevant controls, the latter may be endogenous. We thus distinguish between two sets of control variables - a first set, in which we exclude such potentially endogenous factors, and a second set in which we take them into account. The first set includes information on education, literacy, widowhood, gender, household's maximum education, household's employment situation, access to media, household size, rural or urban locality, Scheduled Castes (SC), Scheduled Tribes (ST) and Other Backward Castes (OBC), muslim, household size, political participation, share of elderly, share of SC, ST, OBC, share of muslims, share of electrified households, share of literate voters in the district.

The complementary set of control variables additionally includes the working status of the elderly person, an indicator of household assets, an indicator of landlessness, and further variables at district level, i.e., Gini index, poverty head count ratio and the share of households that express confidence in local government officials and state governments. At the state level, we further control for share of tax revenue and judicial speed as indicators of state capacity and quality of state-level governance, two factors that might simultaneously influence the transparency of eligibility criteria and the correct selection of beneficiaries. The summary statistics and definitions of all variables are displayed in Appendix 4.C.

4.4.3 Statistical methods

As mentioned above, our main econometric analysis is based on pooled cross sectional regressions allowing our sample to be representative for the total population of the elderly, age-wise eligible for social pension receipt, in both periods of observation. However, results from a panel model with individual fixed effects will be shown in the robustness tests. In all regressions, observations are weighted using corresponding probability weights.

Since our dependent variable is binary, we essentially estimate the probability of being wrongly excluded. We opt for a linear probability model for ease of interpretation. To avoid related heteroscedasticity problems, we use heteroskcedasticity-robust error terms clustered at the district level. For readers preferring the use of non-linear probability models, we replicate the core analysis using a logistic specification in Appendix 4.G. We present marginal effects in both cases to facilitate the comparison.

As a default, our regression models always include an indicator variable for the survey period, which is coded one for the second round of the IHDS (2011/12) and zero for the first round (2004/05). In most specifications we also include state dummies. The year and state fixed effects account for unobservable period- or state-specific heterogeneity. Our empirical model therefore becomes:

$$Y_{it} = \beta_0 + \beta_1 Year_{2012} + \beta_2 TS_{st} + \mathbf{X}'_{it}\boldsymbol{\gamma} + a_s + u_{it} \tag{4.1}$$

where Y_{it} is a binary variable capturing whether individual i is wrongly excluded in period t, $Year_{2012}$ is the period dummy, TS_{st} is the transparency score for state s in period t, a_s is the state fixed effect and $\mathbf{X}$ is a vector of control variables. Our focus is on parameter β_2.

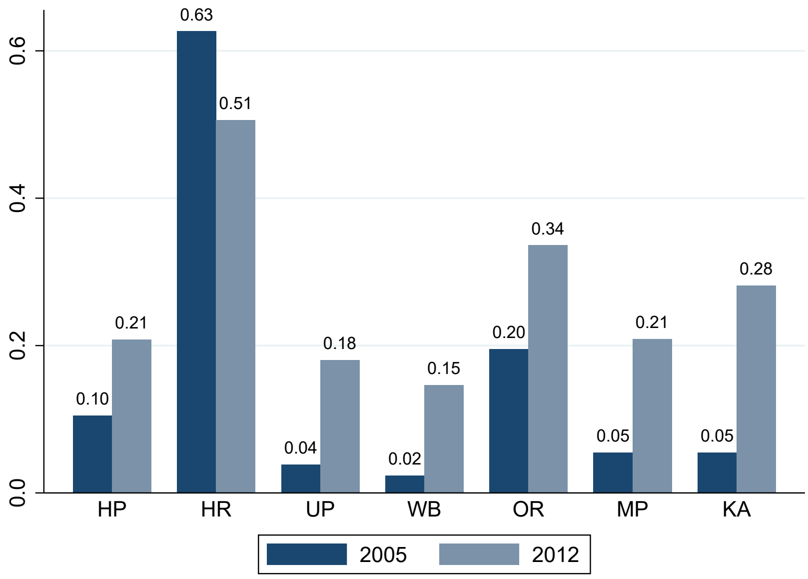
4.5 Results

4.5.1 Descriptive statistics

Before we get to the results of our econometric analysis, we present some relevant descriptive statistics based on the same database. Figure 4.2 shows social pension coverage of the elderly, which reveals strong differences across states and over time. Noticeably, in Haryana, coverage is much higher than in other states. This may be driven by a focus on the elderly within Haryana's social security system following the introduction of the new state pension scheme in 2005 (see Appendix 4.A). However, social pension coverage decreased over time (from 63% in 2005 to 51% in 2012) while it increased in all other states during the same period.

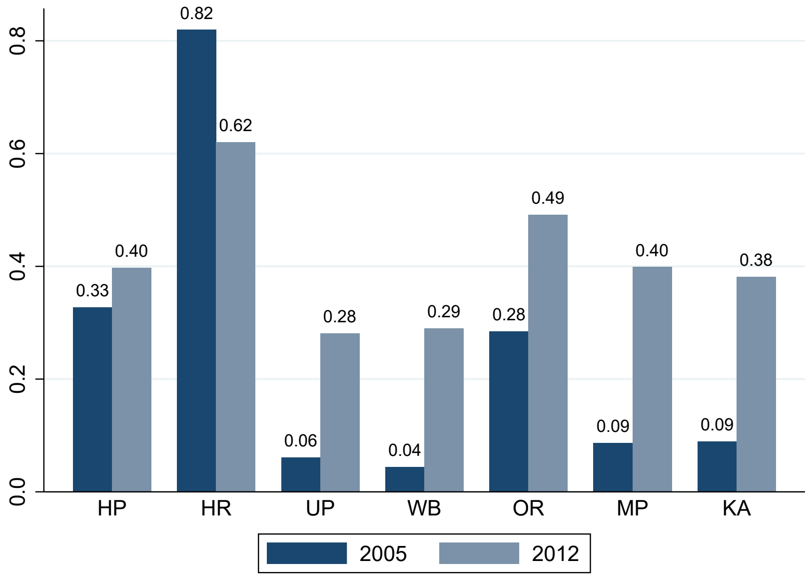
Differences between states and over time could also be related to differences in the prevalence of poverty. However, Figure 4.3 shows that this is not the case. As opposed to the previous figure, Figure 4.3 only considers those elderly living in poor households, namely in households with consumption expenditures below the Tendulkar poverty line. Since this reduces the denominator of the coverage indicator, all rates are higher compared to those in Figure 4.2, but the development over time and the relationships between states remain very similar in the restricted sample. Only Himachal Pradesh and Madya Pradesh move up from the lower end to the middle range among the states covered by our data once poverty is accounted for.

Figure 4.2: Social pension coverage of elderly, by state and year



Himachal Pradesh (HP), Haryana (HR), Uttar Pradesh (UP), West Bengal (WB), Odisha (OR), Madhya Pradesh (MP), Karnataka (KA). Based on observations from pooled cross section. The elderly population includes all individuals who are at least as old as the local eligible age.
Source: IHDS I for 2004-05 and IHDS II for 2011-12.

Figure 4.3: Social pension coverage of elderly poor, by state and year

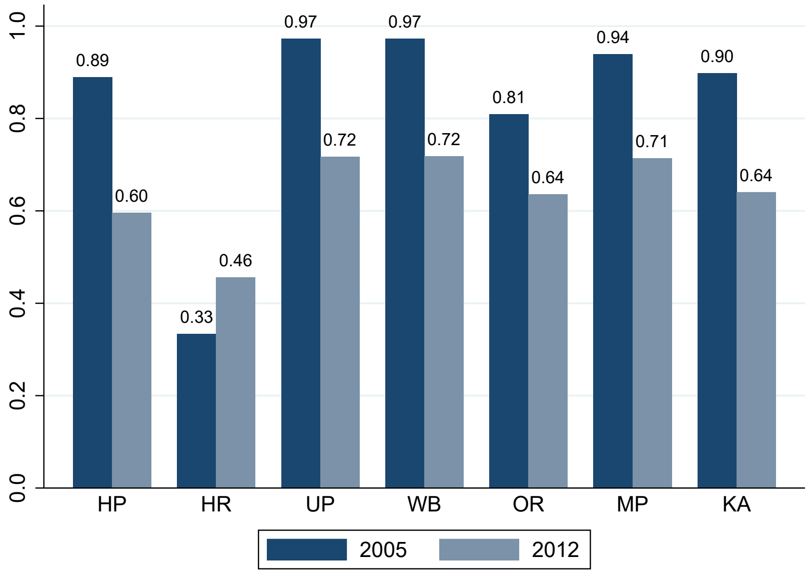


Himachal Pradesh (HP), Haryana (HR), Uttar Pradesh (UP), West Bengal (WB), Odisha (OR), Madhya Pradesh (MP), Karnataka (KA). Based on observations from pooled cross section. The elderly population includes all individuals who are at least as old as the local eligible age.
Source: IHDS I for 2004-05 and IHDS II for 2011-12.

We now look at the exclusion error within each state, and how it evolved over time. Figure 4.4 shows the exclusion error using the sharp criteria, while Figure 4.5 applies the tolerance band.[7] We observe that the exclusion error is extremely high, in 2005 in Uttar Pradesh and West Bengal even close to 100%. In all states except Haryana, the exclusion error in the first period was above 80% and still at or above 60% in 2011-12. The general trends are reversely related to pension coverage. This is what one would expect, since, when the number of available pensions is very low relative to the number of eligible elderly, a large part of them cannot be covered, even if no funding is diverted to ineligible people. The exclusion error calculated with the tolerance band is slightly different but shows a similar pattern.

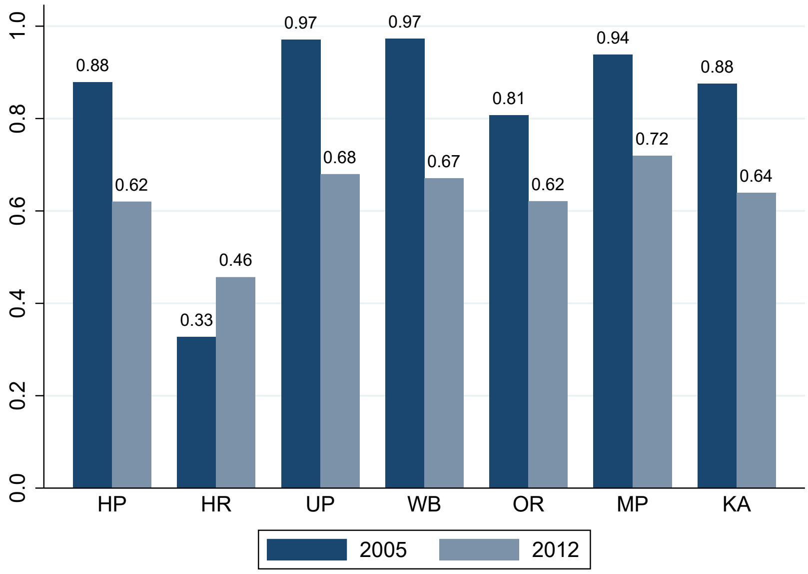
7 While the exclusion error without band is the ratio of the number of eligible individuals in a state not receiving the social pension divided by the number of eligible people, for the exclusion error with band, we consider only clearly eligible people (beyond the tolerance band) both in the numerator and the denominator of this ratio.

Figure 4.4: Exclusion error based on sharp eligibility criteria



Himachal Pradesh (HP), Haryana (HR), Uttar Pradesh (UP), West Bengal (WB), Odisha (OR), Madhya Pradesh (MP), Karnataka (KA). Based on observations from pooled cross section. Source: IHDS I for 2004-05 and IHDS II for 2011-12.

Figure 4.5: Exclusion error based on criteria with tolerance band



Himachal Pradesh (HP), Haryana (HR), Uttar Pradesh (UP), West Bengal (WB), Odisha (OR), Madhya Pradesh (MP), KA (Karnataka). Based on observations from pooled cross section. Source: IHDS I for 2004-05 and IHDS II for 2011-12.

4.5.2 Main econometric outcomes

Our econometric analysis allows us to assess the determinants of exclusion error beyond the obvious link to pension coverage. In particular, it allows us to relate being wrongly excluded measured at the individual level to differences in the transparency of the eligibility criteria. Overall, the empirical results are in line with our expectations. The regressions consistently show that higher transparency is associated with a substantially lower likelihood of being wrongly excluded from social pension benefits. In the following, we present our main results for the representative sample of elderly in the seven Indian states in 2005 and 2012 using the data from the pooled cross section.

In Table 4.1 we show the specifications using our most comprehensive transparency indicator, namely Transparency C. We first run a regression controlling only for the time period. In the second specification we add state fixed effects. After that, we progressively add the different types of controls discussed above, namely pension coverage (Column 3), exogenous covariates (Column 4) and potentially endogenous covariates (Column 5).

The probability of being wrongly excluded decreases by 2-3 percentage points in all models if the transparency score increases by 1 unit (≈ 0.2 standard deviations). In other words, a one standard deviation increase in the transparency score C is associated with a 10-15-percentage point reduction in the probability of being wrongly excluded. For a typical change in eligibility criteria, such as for the national pension scheme IGNOAPS that replaced the destitution criterion by BPL card holding, Transparency C improves by 7 units. According to our estimations, a state following this development (e.g., West Bengal) would decrease the probability of wrong exclusion by 14-21 percentage points. At the higher end, this corresponds to almost half of the average predicted value of 46%.[8]

While these effects are large, no matter which equation we choose, it should be noted that the smallest value comes up in the regression with no covariates except the year dummy. This neglects a number of possibly relevant confounders. For this reason, we believe that the higher values for regressions in which at least state fixed effects, pension coverage and the set of clearly exogeneous controls are taken into account, provide the more plausible estimates.

Table 4.2 shows the same set of specifications, but with our alternative dependent variable including the tolerance band. As expected, this more conservative estimation that does

8 As explained above, this sample average is lower than the exclusion error in the descriptive statistics because the sample also includes a number of non-eligible individuals who, by definition, cannot be wrongly excluded.

not consider anyone as wrongly excluded if the error remains very small, leads to slightly smaller estimates for the effect of transparency. However, the difference between the two estimations is rather negligible. It ranges between 0.006 and 0.5 percentage points. Clearly, an improvement of transparency regarding eligibility criteria is associated with statistically and economically significant improvements in targeting that go way beyond small changes around the eligibility thresholds.

Table 4.1: Transparency measure C and error wrongly excluded without band

	(1)	(2)	(3)	(4)	(5)
Year 2012	-0.190***	-0.178***	-0.125***	-0.143***	-0.0954**
	(0.0184)	(0.0169)	(0.0278)	(0.0303)	(0.0297)
Transparency C	-0.0202***	-0.0243***	-0.0230***	-0.0250***	-0.0282***
	(0.0020)	(0.0030)	(0.0031)	(0.0030)	(0.0026)
Adj. R-Squared	0.11	0.12	0.13	0.15	0.17
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.46	0.46	0.46	0.46	0.46
Between 0 and 1	1.00	1.00	1.00	1.00	1.00
Observations	12414	12414	12414	12412	12412

Dependent variable is wrong exclusion without tolerance band. Standard errors shown in parentheses are clustered at the district level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results are robust to the use of different specifications of the transparency measure. Based on the full model with all controls, Tables 4.3 and 4.4 compare the marginal effects for Transparency C with those of Transparency A (looking only at the count of criteria) and Transparency B (considering only their verifiability). Both of these measures – which have been combined as different dimensions of transparency into Transparency C – are also important on their own. Both are statistically and economically significant. According to Table 4.3, an increase in the number of criteria by one increases the probability of wrong exclusion by 15.5 percentage points (Column 1) and, at a given number of criteria, moving from the most intransparent criterion (destitution) to the clearest criterion (BPL card holding) is associated with a reduction of this probability by about 40 percentage points (7x5.75).

Table 4.2: Transparency measure C and error wrongly excluded with band

	(1)	(2)	(3)	(4)	(5)
Year 2012	-0.214***	-0.222***	-0.162***	-0.176***	-0.103**
	(0.0214)	(0.0184)	(0.0303)	(0.0290)	(0.0299)
Transparency C	-0.0196***	-0.0197***	-0.0182***	-0.0196***	-0.0238***
	(0.0019)	(0.0027)	(0.0027)	(0.0026)	(0.0021)
Adj. R-Squared	0.13	0.15	0.15	0.18	0.21
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.36	0.36	0.36	0.36	0.36
Between 0 and 1	1.00	1.00	1.00	0.99	0.99
Observations	12414	12414	12414	12412	12412

Dependent variable is wrong exclusion with tolerance band. Standard errors shown in parentheses are clustered at the district level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Just as for Transparency C, the more conservative estimation including the tolerance band in Table 4.4 only marginally reduces the size of these effects. All relevant coefficients remain large and highly significant.

Table 4.3: Transparency measures A, B, C, and error wrongly excluded without band

	(1)	(2)	(3)
Year 2012	-0.192***	0.00412	-0.0954**
	(0.0299)	(0.0348)	(0.0297)
Transparency A	-0.155***		
	(0.0145)		
Transparency B		-0.0575***	
		(0.0057)	
Transparency C			-0.0282***
			(0.0026)
Adj. R-Squared	0.17	0.17	0.17
State fixed effects	Yes	Yes	Yes
State coverage	Yes	Yes	Yes
Exogenous covariates	Yes	Yes	Yes
Endogenous covariates	Yes	Yes	Yes
Avg. predicted value	0.46	0.46	0.46
Between 0 and 1	1.00	1.00	1.00
Observations	12412	12412	12412

Dependent variable is wrong exclusion without tolerance band. Standard errors shown in parentheses are clustered at the district level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4: Transparency measures A, B, C, and error wrongly excluded with band

	(1)	(2)	(3)
Year 2012	-0.184***	-0.0174	-0.103***
	(0.0327)	(0.0303)	(0.0299)
Transparency A	-0.128***		
	(0.0122)		
Transparency B		-0.0496***	
		(0.0045)	
Transparency C			-0.0238***
			(0.0021)
Adj. R-Squared	0.21	0.21	0.21
State fixed effects	Yes	Yes	Yes
State coverage	Yes	Yes	Yes
Exogenous covariates	Yes	Yes	Yes
Endogenous covariates	Yes	Yes	Yes
Avg. predicted value	0.36	0.36	0.36
Between 0 and 1	0.99	0.99	0.99
Observations	12412	12412	12412

Dependent variable is wrong exclusion with tolerance band. Standard errors shown in parentheses are clustered at the district level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.5.3 Robustness tests

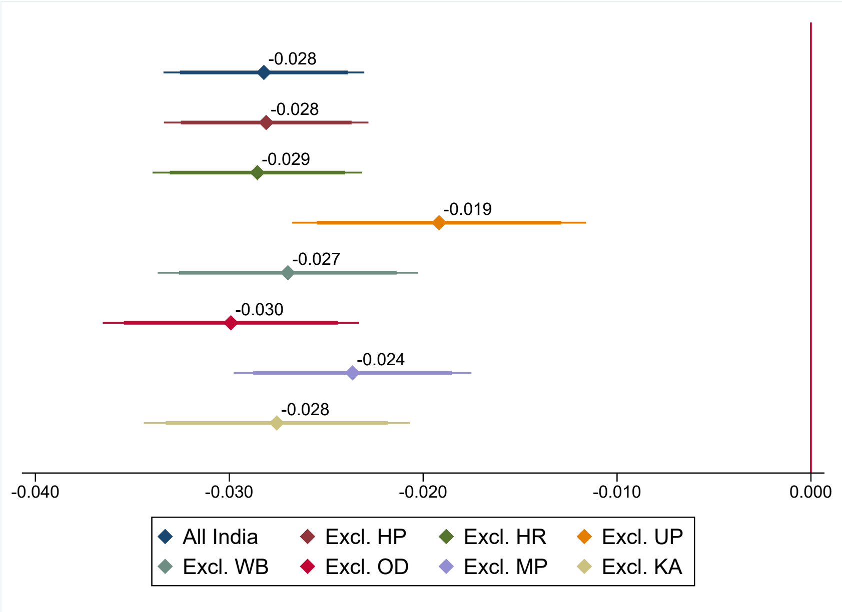
To test the robustness of our results, we conduct a number of complementary analyses. First, we examine whether any specific states drive our results. Second, we examine whether they are robust to a specification using a panel model with individual fixed effects. Third, we use a non-linear specification to control for the changes in coverage. Forth, we examine to what extent unobserved factors correlated with the transparency of eligibility criteria and with the likelihood of being wrongly excluded may influence our results. Fifth, we test whether our findings also hold when we consider a conceptually different measure of the targeting performance of social pensions, and sixth, we apply wild-cluster bootstrapping to account for the fact that our independent variable varies only at the state level and over time. Further robustness tests applying a logistic, rather than a linear probability model are provided in Appendix 4.G.

Outliers at the state level

Potentially, the observed relationship between the transparency of eligibility criteria and the exclusion error could be driven by one particular state. Since Haryana was quite an outlier in the descriptive statistics, showing much better results than the other states in our sample, both regarding coverage and regarding the exclusion error, this may be a possible candidate responsible for driving the results. To see whether such differences are important, we re-run the regression analysis from Table 4.1, Column 5 (full model including all covariates). However, this time, we systematically exclude each of the states one-by-one. Figure 4.6 presents the coefficient estimates for Transparency C for each of the seven regressions. It shows that independently of the state being excluded, we always observe a highly significant and negative coefficient for the net effect of Transparency C ranging from -0.03 (omitting Odisha) to -0.019 (omitting Uttar Pradesh).

Showing the same results for an analysis including the tolerance band again reduces the coefficient estimates, but still shows a sizeable effect of improvements in transparency, no matter which state is excluded (see Figure 4.7). In this more conservative set-up, the effect of Transparency C ranges from -0.026 (omitting Odisha) to -0.011 (omitting Uttar Pradesh).

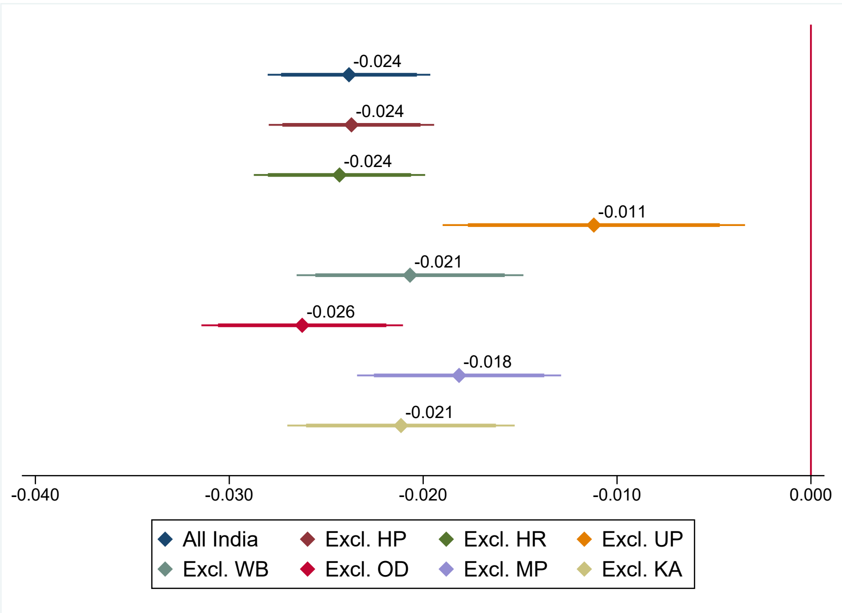
Figure 4.6: Sensitivity of results to included states - without tolerance band



Himachal Pradesh (HP), Haryana (HR), Uttar Pradesh (UP), West Bengal (WB), Odisha (OR), Madhya Pradesh (MP)

Source: IHDS I for 2004-05 and IHDS II for 2011-12.

Figure 4.7: Sensitivity of results to included states - with tolerance band



Himachal Pradesh (HP), Haryana (HR), Uttar Pradesh (UP), West Bengal (WB), Odisha (OR), Madhya Pradesh (MP)

Source: IHDS I for 2004-05 and IHDS II for 2011-12.

The two figures also show that, despite its differences regarding social pension coverage and aggregate exclusion error, Haryana is not an outlier when it comes to the effect of transparency. If at all, Uttar Pradesh might be an outlier here: in both figures the point estimates have a visibly smaller absolute value when Uttar Pradesh is excluded, suggesting that an increase in transparency might be even more relevant there than in other states. However, at least in the estimation without tolerance bands, the confidence intervals for all point estimates largely overlap, so that such differences might simply be an artifact of the specific sample of elderly used in our analysis.

Panel regression

To address potential concerns related to omitted variable bias at the individual level, we now present a panel model that takes into account individual time-invariant heterogeneity through individual fixed effects. As mentioned earlier, the disadvantage of this approach is that the sample is no more representative for the elderly. We have two options to construct the panel. Either we include those that meet the age threshold already in the first period, and who are still alive in the second. This reduces the number of observations considerably. Or we also include all those that become of eligible age only in the second period. This creates some noise as, by definition, these people cannot be wrongly excluded in 2004/5. At the same time, the number of observations in this setting becomes comparable to the number of observations in the repeated cross section models used before. For this reason, we opt for the second choice. Tables 4.9 and 4.10 show the replication of our main results. There are only four columns because state fixed effects are absorbed automatically in the individual fixed effects (perfect multicollinearity).

The estimates are very similar to our earlier results, but with a noticeable reduction in the range of coefficient estimates, which vary little across the different specifications. They come close to those estimates previously obtained for the model with all but the set of potentially endogenous controls. As before, the estimated effect is slightly smaller, but still sizable, when the tolerance band is applied to the computation of the dependent variable.

Table 4.5: Panel regressions without band

	(1)	(2)	(3)	(4)
Year 2012	0.110***	0.0458	-0.0631	-0.159*
	(0.0199)	(0.0351)	(0.0619)	(0.0616)
Transparency C	-0.0251***	-0.0261***	-0.0236***	-0.0241***
	(0.0027)	(0.0027)	(0.0029)	(0.0028)
Adj. R-Squared	0.07	0.08	0.10	0.12
Individual FE	Yes	Yes	Yes	Yes
State coverage	No	Yes	Yes	Yes
Exogenous covariates	No	No	Yes	Yes
Endogenous covariates	No	No	No	Yes
Avg. predicted value	0.34	0.34	0.34	0.34
Between 0 and 1	1.00	1.00	0.98	0.58
Observations	12908	12908	12908	12908
Number of id	6454	6454	6454	6454

Dependent variable is wrong exclusion without tolerance band. Standard errors shown in parentheses are clustered at the district level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.6: Panel regressions with band

	(1)	(2)	(3)	(4)
Year 2012	0.0939***	0.0649	0.0160	-0.0228
	(0.0168)	(0.0357)	(0.0576)	(0.0567)
Transparency C	-0.0217***	-0.0221***	-0.0201***	-0.0208***
	(0.0022)	(0.0023)	(0.0025)	(0.0023)
Adj. R-Squared	0.07	0.07	0.10	0.12
Individual FE	Yes	Yes	Yes	Yes
State coverage	No	Yes	Yes	Yes
Exogenous covariates	No	No	Yes	Yes
Endogenous covariates	No	No	No	Yes
Avg. predicted value	0.24	0.24	0.24	0.24
Between 0 and 1	1.00	1.00	0.96	0.64
Observations	12908	12908	12908	12908
Number of id	6454	6454	6454	6454

Dependent variable is wrong exclusion with tolerance band. Standard errors shown in parentheses are clustered at the district level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Alternative control for coverage

As we have seen in the descriptive statistics, social pension coverage changed considerably between the two periods of observation, and this change may affect our results if changes in coverage are correlated with reforms of the eligibility criteria. So far, we have taken this into account by simply controlling for state-wise coverage rates. However, if the effect of coverage is non-linear, this simple control strategy may leave some room for remaining omitted variable bias. We thus propose an alternative non-linear approach to eliminate the effect of increased coverage from our estimation.

Tables 4.7 and 4.8 show the regressions including the covariate state coverage with its polynomials up to the third degree. Specifications (1)-(3) are without covariates, while (4)-(6) include all but the state-level covariates. The issue is that we do not have much variation at the state level so that additional variables for state coverage along with all the previously included state-level covariates lead to severe collinearity problems.

Table 4.7: Polynomial coverage control without band

	(1)	(2)	(3)	(4)	(5)	(6)
Year 2012	-0.137***	-0.179***	-0.179***	-0.170***	-0.136**	-0.149***
	(0.018)	(0.030)	(0.035)	(0.023)	(0.039)	(0.040)
Transparency C	-0.022***	-0.022***	-0.013***	-0.024***	-0.024***	-0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Adj. R-Squared	0.12	0.12	0.13	0.15	0.15	0.16
Avg. predicted value	0.46	0.46	0.46	0.46	0.46	0.46
State_coverage	Yes	Yes	Yes	Yes	Yes	Yes
$State\_coverage^2$	No	Yes	Yes	No	Yes	Yes
$State\_coverage^3$	No	No	Yes	No	No	Yes
Exogenous covariates	No	No	No	Yes	Yes	Yes
Endogenous covariates	No	No	No	Yes	Yes	Yes
Between 0 and 1	1.00	1.00	1.00	1.00	1.00	1.00
Observations	12414	12414	12414	12412	12412	12412

Dependent variable is wrong exclusion without tolerance band. Standard errors shown in parentheses are clustered at the district level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

While adding the square term in Columns (2) and (5) does not change the earlier results, the point estimate of the transparency measure shrinks considerably when adding the

Table 4.8: Polynomial coverage control with band

	(1)	(2)	(3)	(4)	(5)	(6)
Year 2012	-0.194***	-0.247***	-0.246***	-0.217***	-0.176***	-0.193***
	(0.018)	(0.030)	(0.034)	(0.025)	(0.038)	(0.041)
Transparency C	-0.020***	-0.020***	-0.009**	-0.021***	-0.021***	-0.009**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Adj. R-Squared	0.13	0.13	0.15	0.17	0.17	0.18
Avg. predicted value	0.36	0.36	0.36	0.36	0.36	0.36
$State\_coverage$	Yes	Yes	Yes	Yes	Yes	Yes
$State\_coverage^2$	No	Yes	Yes	No	Yes	Yes
$State\_coverage^3$	No	No	Yes	No	No	Yes
Exogenous covariates	No	No	No	Yes	Yes	Yes
Endogenous covariates	No	No	No	Yes	Yes	Yes
Between 0 and 1	1.00	1.00	1.00	0.99	0.99	0.99
Observations	12414	12414	12414	12412	12412	12412

Dependent variable is wrong exclusion with tolerance band. Standard errors shown in parentheses are clustered at the district level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

third polynomial. Adding a forth and fifth polynomial does not lead to relevant further changes (not shown). While the point estimates are smaller, they remain relevant, both economically and statistically.

If we again take the relatively typical example of West Bengal where Transparency C changes by 7 points, even the smallest point estimates suggests a corresponding reduction of the probability of wrong exclusion by 9.1 percentage points (Table 4.7, Column (3)), and of 4.9 percentage points when allowing for the tolerance band (Table 4.8, Columns (3) and (6)).

Selection on unobservables

Despite our efforts to control for observable factors at individual, household, village, district and state level, the estimated effects can still be biased by unobservables. If these unobservable factors are correlated with the transparency measure and with the likelihood of being wrongly excluded, we might just observe a spurious correlation. We closely follow Nunn & Wantchekon (2011) to assess how likely it is that our estimates are biased by unobservable factors. The basic idea goes back to Altonji et al. (2005) showing that selection on observables can be seen as a measure to assess selection on unobservables.

The relevant measure called Selection Ratio can be derived from two regressions. One regression includes a restricted set of control variables and the other one a full set of control variables. Let us call the estimated coefficient of interest from the regression with the restricted set of control variables $\hat{\beta_R}$ (R for restricted), and from the regression with the full set of control variables $\hat{\beta_F}$ (F for full). Based on these coefficients we can calculate the Selection Ratio:

$$\text{Selection Ratio} = |\frac{\hat{\beta_F}}{\hat{\beta_R} - \hat{\beta_F}}| \tag{4.2}$$

The Selection Ratio indicates how strong selection on unobservables would have to be to explain away the estimated effect. The ratio increases in absolute values of $\hat{\beta_F}$ since a larger coefficient for the variable of interest implies that selection on unobservables would need to explain a larger effect. It decreases in absolute values of $\hat{\beta_R} - \hat{\beta_F}$ because a smaller difference between the coefficient of interest from the restricted model and the coefficient of interest from the full model means that the estimate is less affected by the addition of control variables. Therefore, the selection on unobservables compared to selection on observables needs to be stronger to explain the full effect (Nunn & Wantchekon 2011, p. 3238). In the following, we present the Selection Ratio for two restricted sets of control variables and two full sets of control variables.

The first restricted set (R1) includes only year fixed effects. The second restricted set (R2) includes year and state fixed effects. The first full set (F1) includes year fixed effects, state fixed effects, state coverage and exogenous control variables. The second full set (F2) includes year fixed effects, state fixed effects, state coverage as well as exogenous and endogenous control variables. All these coefficients have already been computed for the presentation of our main results in Table 4.1.

Table 4.5 again reports these regression coefficients now labeled $\hat{\beta_R}$ and $\hat{\beta_F}$, and the corresponding Selection Ratios. The ratio varies between 3.52 when we compare the coefficients for R1 and F2 (second row) and 38.64 when we compare the coefficients for R2 and F1. This implies that the effect of selection on unobservables would have to be at least 3.52 times larger than the effect of the selection on observables to explain away the estimated effects.

With the inclusion of multiple control variables at various levels including controls for social pension coverage, state governance and population size (and many others), we have already accounted for a large number of potentially confounding factors. We thus believe that it is highly unlikely that selection on unobservables entirely drives the estimated effect of transparency on the likelihood of being wrongly excluded.

Table 4.9: Test for selection on unobservables

Controls in the restricted set	Controls in the full set	$\hat{\beta}_R$	$\hat{\beta}_F$	Selection Ratio
R1: Year FE	F1: Year FE, state FE, state coverage and exogenous controls	-0.020	-0.025	5.23
R1: Year FE	F2: Year FE, state FE, state coverage, exogenous controls, and endogenous controls	-0.020	-0.025	4.95
R2: Year FE and state FE	F1: Year FE, state FE, state coverage and exogenous controls	-0.024	-0.025	38.64
R2: Year FE and state FE	F2: Year FE, state FE, state coverage, exogenous controls, and endogenous controls	-0.024	-0.025	25.62

Alternative dependent variable: correct selection

While we have already considered two dependent variables - wrong exclusion based on sharp eligibility criteria and wrong exclusion measured with a tolerance band - both are based on the same general concept of mistargeting. As the limited number of pensions available in 2004-05 prevents us from studying wrong inclusion, this is no possible alternative. However, as a complement to wrong exclusion, we can also examine correct inclusion, or, more generally, correct selection into the pension schemes.

While wrong exclusion is currently the predominant concern, this complementary measure may provide a relevant additional perspective for several reasons. First, it may be a less noisy targeting indicator in a situation where much of the wrong exclusion is simply driven by the fact that the number of available pensions does not match the number of eligible elderly. Second, many individuals might be counted as wrongly excluded because they fulfill the eligibility criteria, but simply do not apply. Whether this happens because they are discouraged from applying or because they are too poor, uneducated and vulnerable to apply (or do not even know about the pension schemes), they rightly increase the measure for wrong exclusion. However, given numerous problems with the targeting of the BPL card, people may well be formally eligible in terms of age and BPL status, but not actually be poor. This share is indeed non-negligible, as we show in Figure 4.9 of Appendix 4.H. For some of these people, applying for the limited benefits provided by the social pension scheme may simply not be worth the effort, and they may hold the BPL card for other reasons (e.g., tax evasion or access to subsidized food). In this case, the exclusion error will appear more problematic than it actually is. The measures of correct inclusion or generally, correct selection, are not affected by such problems.

We thus re-run our main set of equations measuring targeting performance by correct selection into the pension schemes. Observations for which the value of this variable is 1 refer either to individuals who are eligible according to official eligibility criteria and receive social pension benefits, or to those who are ineligible and do not receive social pension benefits. The value of this variable is 0 otherwise.

Table 4.10 confirms that an increase in the transparency of the eligibility criteria has an economically and statistically significant effect on targeting performance. In fact, the coefficient estimates are not very different from those we obtained before. The sign change is only due to the fact that our dependent variable is now formulated in a positive way, rather than as an error. Increasing the transparency of eligibility criteria by one unit is associated with an increase in the likelihood of a correct selection decision (correct inclusion or correct exclusion) by 1.7-2.4 percentage points. Put differently, a one standard deviation increase in the transparency score is associated with an 8.5-12 percentage points increase in the likelihood of correct selection. The comparable values we had obtained using wrong exclusion as the dependent variable were 10-15 percentage points.

Table 4.10: Alternative dependent variable

	(1)	(2)	(3)	(4)	(5)
Year 2012	0.185***	0.177***	0.162***	0.163***	0.161***
	(0.0170)	(0.0162)	(0.0299)	(0.0307)	(0.0295)
Transparency C	0.0166***	0.0194***	0.0190***	0.0208***	0.0210***
	(0.0022)	(0.0028)	(0.0028)	(0.0027)	(0.0028)
Adj. R-Squared	0.09	0.10	0.10	0.12	0.13
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.51	0.51	0.51	0.51	0.51
Between 0 and 1	1.00	1.00	1.00	1.00	1.00
Observations	12414	12414	12414	12412	12412

Dependent variable is correctly included. Standard errors shown in parentheses are clustered at the district level.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Wild-cluster bootstrapping

Finally, we address the concern that clustering of errors at district levels could lead us to be overly confident of the statistical significance of our results. Indeed, since our indicators of transparency do not vary across districts, our estimated standard errors clustered at the district level may lead to downward biased estimates of the standard errors (Angrist & Pischke 2009). While traditional clustering at the state level is not possible in our context, because the number of clusters would be too small to reasonably expect convergence, wild-cluster bootstrapping circumvents this problem (Cameron et al. 2008). Tables 4.11 and 4.12 show our results when using this bootstrapping procedure for clusters at the state level. As compared to Tables 4.1 and 4.2, the presentation omits the specification without state fixed effects since the latter are particularly important in any setting that cares for possible similarities between observations within states. The top-row in Tables 4.11 and 4.12 report the relevant coefficients along with the original standard errors, while the following line shows the bootstrapped standard errors used for the present analysis. While the standard errors change, the relevant coefficient estimates remain the same, and all of them remain significant at the 1% level.

Table 4.11: Estimation with wild cluster-bootstrapping standard errors - without tolerance band

	(1)	(2)	(3)	(4)
Transparency C	-0.0243***	-0.0230***	-0.0250***	-0.0253***
	(0.0030)	(0.0031)	(0.0030)	(0.0030)
Bootstrapped SE	0.0041	0.0051	0.0043	0.0044
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State coverage	No	Yes	Yes	Yes
Exogenous controls	No	No	Yes	Yes
Endogenous controls	No	No	No	Yes
Observations	12414	12414	12412	12412

Dependent variable is wrong exclusion without tolerance band. Standard errors shown in parentheses are clustered at the district level. The bootstrapped standard error indicates the standard error after applying wild cluster bootstrapping.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.12: Estimation with wild cluster-bootstrapping standard errors - with tolerance band

	(1)	(2)	(3)	(4)
Transparency C	-0.0197***	-0.0182***	-0.0196***	-0.0196***
	(0.0027)	(0.0027)	(0.0026)	(0.0026)
Bootstrapped SE	0.0052	0.0064	0.0062	0.0062
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State coverage	No	Yes	Yes	Yes
Exogenous controls	No	No	Yes	Yes
Endogenous controls	No	No	No	Yes
Observations	12414	12414	12412	12412

Dependent variable is wrong exclusion with tolerance band. Standard errors shown in parentheses are clustered at the district level. The bootstrapped standard error indicates the standard error after applying wild cluster bootstrapping.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.5.4 Discussion

In sum, none of the robustness tests challenges any of our results. Clearly, the transparency of eligibility criteria matters for social pension targeting, and it does so in both dimensions: the number of criteria and their clarity or verifiability.

As our analysis focuses on a physically weak and often uneducated target group, namely the elderly poor, even with more transparent criteria, it may be difficult for them to claim their rights and monitor correct selection processes unless they receive external support through family members or NGOs. Hence, the effects we observe here may represent a lower bound for the effect that a reform of eligibility criteria might achieve in other social welfare schemes that target working age population or entire households.

If eligibility is determined based on criteria that themselves require appropriate targeting – such as, in our case, BPL card holding – the targeting of these underlying criteria should be similarly reformed. This is in line with current policy efforts in India. Indeed, the Indian government is well-aware of the problems related to BPL identification processes (Government of India et al. 2009, p.17ff). In 2011, the Socio-Economic and Caste Census (SECC) was launched with the primary objective to revise the identification of BPL households. It uses a variety of asset- and income-based criteria along with direct exclusion and inclusion conditions that are meant to simplify the assessment. The new criteria were formally adopted by the Ministry of Rural Development in January 2017 (Government of India 2017). It remains to be seen to what extent they will improve upon the status quo.

4.6 Conclusion

Due to wide-spread corruption, local elite capture, clientelism, lack of information and lack of administrative capacity, the targeting of public welfare programs remains a daunting challenge in many developing countries. These problems can be expected to be even greater and harder to remedy, for programs like social pensions targeted to the elderly poor, who are generally less well-educated, less mobile and less vocal when it comes to claiming their rights.

Based on the exploration of extensive administrative information, two rounds of data from the India Human Development Survey, and numerous interviews helping us to interpret the information at hand, we analyzed the question whether the targeting of social pensions could be improved by using more transparent eligibility criteria. Drawing together different dimensions of transparency discussed in the literature into a single indicator, we show that indeed, the effect of an improvement in the transparency of eligibility criteria is both statistically and economically significant. In our main specifications, the effect of a one-standard deviation increase in the transparency indicator is associated with a reduction of the probability to be wrongly excluded by 10-15 percentage points. We can show that these effects are due to different dimensions of transparency, notably a reduced number of different criteria as well as better verifiability for each criterion applied. Each of them has a substantial effect on targeting performance. We also show that this strong effect is not just related to avoiding errors at the margin. To do so, we construct a new measure for wrong exclusion that applies a tolerance band around all relevant eligibility criteria. The resulting more conservative measure for the effect of transparency is only slightly smaller than the one based on the initial estimation.

These results are robust to a large number of additional specifications. In particular, they do not depend on the inclusion of individual states, they hold in a repeated cross section analysis as well as in a panel model with individual fixed effects, they remain valid when we use a non-linear approach to control for pension coverage, and they are robust to different approaches of clustering. In addition, we can show that it is highly unlikely that unobserved confounders are driving these effects, and that the results also hold when we consider an alternative dependent variable, which is not based on wrong exclusion, but on correct selection into the pension scheme.

This suggests a systematic reform of eligibility criteria, not just for social pensions, but also for other social welfare schemes. Given the particularities of the target population for a pension scheme, the effects on other schemes might be even stronger. In any case, the proposed reform is not very costly as it only consists in selecting a more transparent set of criteria and disseminating the related information. In the long run, due to reduced assessment cost, when using the simplified criteria, such a reform may even be financially rewarding. This suggests that the cost-effectiveness of such a reform would be very high.

Appendix

4.A State-level eligibility criteria

State	Name of scheme	Eligibility criteria 2004-05	Eligibility criteria 2011-12
Himachal Pradesh	IGNOAPS	Age 65 years or above, destitute	Age 60 years or above, BPL card holding
	State Old Age Pension Scheme	Age 60 years or above, individual annual income $\leq$ Rs. 6000 and if the elderly has adult children their income should not exceed Rs. 11000	Age 60 years or above, individualdoes not have anyone to take care of him/her, individual annual income $\leq$ Rs. 9000 or total annual family income $\leq$ Rs. 15000 excluding his/her own income
Sources:		Gov. of HP (undated(a))	Gov. HP (undated(b))
Haryana	IGNOAPS	Age 60 years or above, personal income from all sources together with spouse's income $\leq$ Rs. 50.000 per annum, domicile requirement	Age 60 years or above, BPL card holding
	Old Age Samman Allowance (since November 2005)	Scheme did not exist.	Age 60 years or above, personal income from all sources together with spouse's income $\leq$ Rs. 200,000 per annum for rural and urban areas
Sources:		Gov. of HR (2006, 2011)	Gov. of HR (undated(a))

State	Name of scheme	Eligibility criteria 2004-05	Eligibility criteria 2011-12
Uttar Pradesh	IGNOAPS	Age 65 years or above, destitute, domicile requirement	Age 60 years or above, BPL card holding for rural areas, BPL or Antyodaya card holding for urban areas, resident of UP
	Kisan Pension Scheme (valid up to May 2007)	Age 60-64 years, land holding $\leq$ 3.25 acre for rural areas or individual income < Rs. 12000 per annum for urban areas, domicile requirement	Scheme did not exist.
	MAHAMAYA (valid during 2007 - 2012)	Scheme did not exist.	Age 60 years or above, BPL card holding for rural areas, BPL or Antyodaya card holding for urban areas, domicile requirement
Sources:		Gov. of UP (undated), Comptroller and Auditor General of India, (2009)	Gov. of UP (2010a, 2010b, 2010c)
West Bengal	IGNOAPS	Age 65 years or above, destitute	Age 60 years or above, BPL card holding
Sources:		Gov. of WB (undated)	
Madhya Pradesh	IGNOAPS	Age 65 years or above, destitute	Age 60 years or above, BPL card holding
	Samagra Social Security Pension Scheme	Age 60 or above, destitute	Age 60 years or above, BPL card holding or landless and destitute
Sources:		Gov. of MP (undated)	Gov. of MP (2012, 2013)
Odisha	IGNOAPS	Age 65 years or above, destitute	Age 60 years or above, BPL card holding
	Madhu Babu Pension Yojana (since 2008)	Scheme did not exist.	Age 65 years or above, destitute or age 60 years or above and annual household income from all sources $\leq$ Rs. 24000, domicile requirement
Sources:		Gov. of OR (2008)	Gov of OR (undated (a), (b))
Karnataka	IGNOAPS	Age 65 years or above, BPL card holding, annual income < Rs.6000 per annum	Age 60 years or above, BPL card holding
	Sandhya Suraksha Yojana (since 2007)	Scheme did not exist.	Age 60 years or above, annual household income $\leq$ Rs 20000
Sources:		Rajasekhar et al. (2009), Chathukulam et al. (2012) Gov of KA (undated)	webindia123.com (2007)

4.A.1 References for state-level eligibility criteria

We collected the administrative information on state-level eligibility criteria primarily from state government websites. Since state websites are updated frequently, we provide below the references with links to the web archive (http://web.archive.org/) to ensure that they function in the longer run. We further provide all sources for administrative information on state-level eligibility criteria used for this study in an online-appendix: State-level eligibility criteria and sources

4.A.2 Himachal Pradesh

Himachal Pradesh 2004-05

Government of Himachal Pradesh (undated(a)) Evaluation Study of Beneficiaries under Old Age Widow and National Security Pension Scheme. Shimla: Evaluation Division, Planning Department. Available at https://web.archive.org/web/20160508190345/http://hpplanning.nic.in/beneficiaries%20under%20old%20age%20widow%20and%20national%20security%20pension%20scheme%20-%20himachal%20pradesh.pdf, accessed on 15 September 2020.

Himachal Pradesh 2011-12

Government of Himachal Pradesh (undated(b)) Social Security Pension Schemes. Shimla: Directorate of Social Justice and Empowerment. Available at http://web.archive.org/web/20170222012249/http://admis.hp.nic.in/himachal/welfare/SocialSecurityPensionSchemesOct2013_A1b.pdf, accessed on 15 September 2020.

4.A.3 Haryana

Haryana 2004-05

Government of Haryana, (2006) Notification [regarding the Old Age Allowance Scheme] No. 1988-SW4(2006) dated 20 September 2006, extracted from Haryana Government Gazette, dated 7th November 2006, Social Welfare Department. Available at http://web.archive.org/web/20161020013151/http://socialjusticehry.gov.in/Website/oasa(1).pdf, accessed on 15 September 2020.

Government of Haryana, (2011) Notification [regarding the Old Age Samman Allowance Scheme] No. 458-SW(4)2011 dated 10 June 2011, extracted from Haryana Government Gazette, dated 10 June 2011, Chandigarh: Social Justice & Empowerment Department. Available at http://web.archive.org/web/20160222055746/http://socialjusticehry.gov.in/SocialJusticeNotification.pdf, accessed on 15 September 2020.

Government of Haryana, (undated(b)) Pension schemes. Chandigarh: Directorate of Social Justice & Empowerment. Available at https://web.archive.org/web/20160729233028/http://socialjusticehry.gov.in/pension11.aspx, accessed on 15 September 2020.

Haryana 2011-12

Government of Haryana, (undated(a)) Social security schemes. Chandigarh: Directorate of Social Justice & Empowerment. Available at http://web.archive.org/web/20170215085709/http://socialjusticehry.gov.in/Website/SocialSecurity_PensionSchemes.pdf, accessed on 15 September 2020.

4.A.4 Uttar Pradesh

Uttar Pradesh 2004-05

Government of Uttar Pradesh (undated) Indira Gandhi National Old Age Pension Scheme. Department of Social Welfare: Lucknow. Available at https://web.archive.org/web/20160708031602/http://sspy-up.gov.in/pdf/oap_scm.pdf, for application format, https://web.archive.org/web/20160708152801/http://sspy-up.gov.in/AboutScheme/app_frmt_oap.pdf, accessed on 15 September 2020.

Comptroller and Auditor General of India, (2009) Report on the audit of expenditure incurred by the Government of Uttar Pradesh. New Delhi: CAG, Government of India. Available at https://cag.gov.in/sites/default/files/audit_report_files/Uttar_Pradesh_Civil_2009.pdf, accessed on 15 September 2020.

Uttar Pradesh 2011-12

Government of Uttar Pradesh (2010a) Government Order on Mahamaya. GO No. 2359/26- 2-201 0- 3MS/10, dated 3 August 2010. Available at https://web.archive.

org/web/20160607124742/http://swd.up.nic.in/pdf/GO03082010_final.pdf, for application format, No. 2359/26- 2-201 0- 3 MS/10. Lucknow: Social Welfare Commissioner. Available at https://web.archive.org/web/20160607123712/http://swd.up.nic.in/GO130920100001.pdf, accessed on 15 September 2020.

Government of Uttar Pradesh (2010b) Government Order on Mahamaya. GO No. 2530/26-2-2010-3MS/2010, dated 10 August 2010. Lucknow: Social Welfare Commissioner. Available at https://web.archive.org/web/20160607123706/http://swd.up.nic.in/10082010.pdf, accessed on 15 September 2020.

Government of Uttar Pradesh (2010c) Government Order on Mahamaya. GO No. 2400/26-2-2010-3MS/10, dated 3 August 2010. Lucknow: Social Welfare Commissioner. Available at https://web.archive.org/web/20160607124742/http://swd.up.nic.in/pdf/GO03082010_final.pdf, accessed on 15 September 2020.

4.A.5 West Bengal

Government of West Bengal (undated) Social Security Schemes. Kolkata: Department of Panchayats & Rural Development. Overview page available at http://web.archive.org/web/20160627182135/http://wbprd.gov.in/HtmlPage/SSECURITY.aspx, accessed on 15 September 2020, see PDF for more detailed information.

4.A.6 Madhya Pradesh

Madhya Pradesh 2004-05

Government of Madhya Pradesh (undated) (in Hindi) Samajik Sahayata ki Bistrut Jankari. Bhopal: Social Justice Department. Available at http://web.archive.org/web/20160513082657/http://socialjustice.mp.gov.in/Portal/Public/Scheme_Details.aspx?ID=1, accessed on 15 September 2020.

Madhya Pradesh 2011-12

Government of Madhya Pradesh (2012) (in Hindi) Samajik Suraksha Bruddhabastha Pension Yojana. Bhopal: Social Justice Department. Originally available at http:

//pensions.samagra.gov.in/SSPDetails.aspx, accessed on 13 July 2016, see PDF documentation online.

Government of Madhya Pradesh (2013) (in Hindi) Samajik Suraksha Bruddhabastha Pension Yojana. Bhopal: Social Justice Department. Originally available at http://pensions.samagra.gov.in/IGNOAPDetails.aspx, accessed on 13 July 2016, see PDF documentation online.

4.A.7 Odisha

Odisha 2004-05

Government of Odisha (2008) The Odisha Gazette. Notification No. 11–I-SD-50/2007-WCD. Cuttack: Women and Child Development Department. January 4, 2016. Available at http://web.archive.org/web/20161130174447/http://odisha.gov.in/govtpress/pdf/2008/15.pdf, accessed on 15 September 2020.

Odisha 2011-12

Government of Odisha (undated (a)) Indira Gandhi National Old Age Pension. Bhubaneswar: Women And Child Development Department. Available at http://web.archive.org/web/20160605093834/http://wcdodisha.gov.in/node/60, accessed on 15 September 2020.

Government of Odisha (undated (b)) Madhu Babu Pension Yojana. Bhubaneswar: Women And Child Development Department. Available at http://web.archive.org/web/20160529181623/http://wcdodisha.gov.in/node/64, accessed on 15 September 2020.

4.A.8 Karnataka

Rajasekhar, D., G. Sreedhar, N.L. Narasimha Reddy, R.R. Biradar, and R. Manjula, (2009) Delivery of Social Security and Pension Benefits in Karnataka. Institute for Social & Economic Change, Bengaluru. Report submitted to Directorate of Social Security and Pensions Department of Revenue, Government of Karnataka. Available at http://dssp.kar.nic.in/news.pdf, accessed on 15 September 2020.

Chathukulam, Jos, Veerasekharappa, Rekha V., and C.V. Balamurali, (2012) Evaluation of Indira Gandhi National Old Age Pension Scheme (IGNOAPS) in Karnataka. Centre for Rural Management, Kottayam, Kerala. Report submitted to Ministry of Rural Development, Government of India, New Delhi. August 2012. Available at http://crmindia.org/files/KaIGNOAPS.pdf, accessed on 15 September 2020.

Karnataka 2004-05

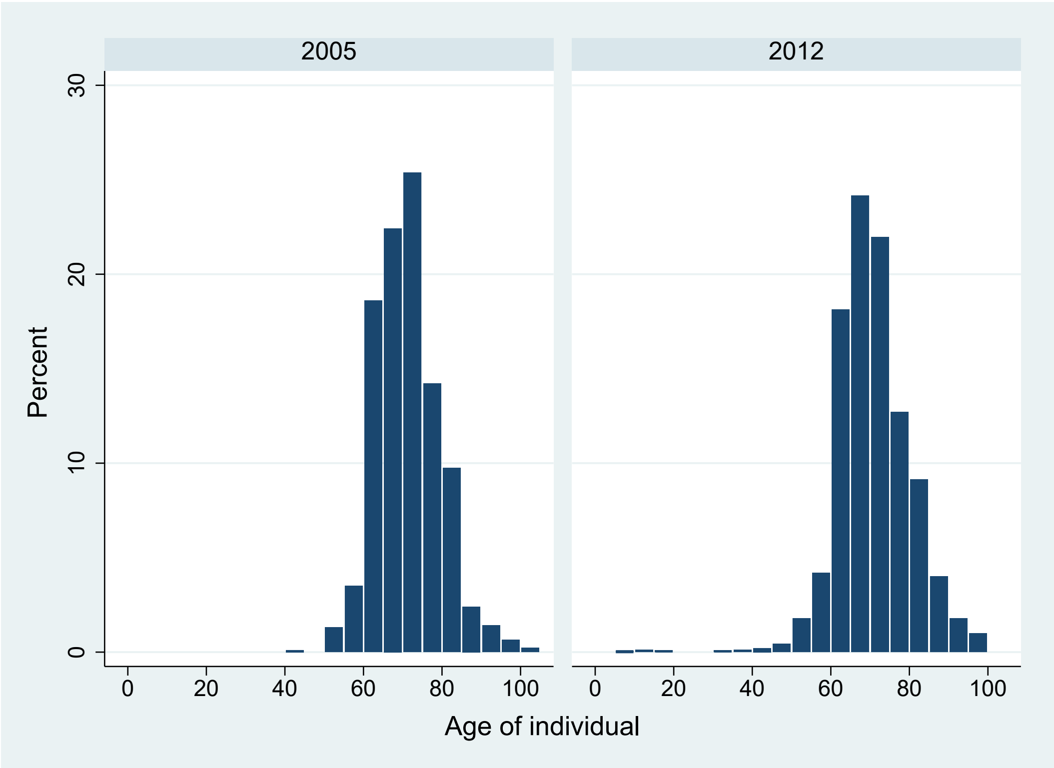
Government of Karnataka (undated) Sandhya Suraksha Yojana. Available at http://web.archive.org/web/20150522020009/http://dssp.kar.nic.in/sandhyasur.html, accessed on 15 September 2020.

Karnataka 2011-12

webindia123.com (2007) K'taka Govt to launch 'Sandhya Suraksha Yojana' on July 29. Mysore, July 4, 2007. Available at http://news.webindia123.com/news/ar_showdetails.asp?id=707040701&cat=&n_date=20070704, accessed on 15 September 2020.

4.B Age distribution

Figure 4.8: Age distribution of social pension beneficiaries



Source: Authors' illustration, descriptive statistics based on IHDS-I for 2004-05 and IHDS-II for 2011-12.

4.C Variable description and sources

VARIABLES	2004-05 mean	2004-05 se	2011-12 mean	2011-12 se	Measurement level	Definition	Data source
Error excluded	0.646	0.012	0.355	0.008	Individual	Dummy equal to 1 if individual does not receive social pension but fulfills the locally relevant eligibility criteria	IHDS & admin. info
Error excluded band	0.560	0.012	0.248	0.007	Individual	Dummy equal to 1 if individual does not receive social pension but fulfills the locally relevant eligibility criteria using tolerance band	IHDS & admin. info
Correctly included or excluded	0.331	0.012	0.600	0.009	Individual	Dummy equal to 1 if individual receives a social pension and fulfills the locally relevant eligibility criteria or does not receive a social pension and does not fulfill the locally relevant eligibility criteria	IHDS & admin. info
Transparency A	2.465	0.037	2.432	0.016	State	Transparency score A= 5 - number of eligibility criteria (clauses and sub-clauses). Range is 1-4. For a detailed explanation, see Appendix D.	Admin. info
Transparency B	1.654	0.023	5.727	0.049	State	Transparency score B = Verifiability score of the least verifiable category of eligibility criteria applied. Range is 1-8. For a detailed explanation, see Appendix D.	Admin. info
Transparency C	19.573	0.086	24.595	0.087	State	Transparency score C = Weighted sum of eligibility criteria whereby weights are based on verifiability score. Range is 13-29.	Admin. info
Pension recipient	0.095	0.006	0.224	0.007	Individual	Dummy equal to 1 if individual receives social pension	IHDS
Age	71.210	0.187	70.271	0.152	Individual	Age of the individual	IHDS
Female	0.470	0.013	0.497	0.009	Individual	Dummy equal to 1 if individual is female	IHDS
Literate	0.338	0.011	0.378	0.008	Individual	Dummy equal to 1 if individual can read and write	IHDS

VARIABLES	2004-05 mean	2004-05 se	2011-12 mean	2011-12 se	Measurement level	Definition	Data source
Widowed	0.403	0.012	0.403	0.009	Individual	Dummy equal to 1 if individual is widowed	IHDS
Working	0.396	0.013	0.299	0.009	Individual	Dummy equal to 1 if individual is working at least 240 hours per year	IHDS
BPL card	0.277	0.011	0.434	0.009	Household	Dummy equal to 1 if household holds a BPL card	IHDS
Household assets	10.908	0.128	13.136	0.113	Household	Number of household assets owned	IHDS
Landless	0.349	0.011	0.410	0.009	Household	Dummy equal to 1 household is landless	IHDS
Permanent job	0.099	0.006	0.144	0.006	Household	Dummy equal to 1 if any household member has a permanent job	IHDS
Household max. education	7.725	0.133	8.179	0.098	Household	Education level of the most educated person in the household.	IHDS
Local government connection	0.100	0.006	0.328	0.009	Household	Dummy equal to 1 if household has a direct connection to the local government	IHDS
Household size	6.533	0.090	5.586	0.050	Household	Number of persons sharing one kitchen	IHDS
Urban	0.192	0.007	0.259	0.006	Household	Dummy equal to 1 if household lives in urban area	IHDS
Share state confidence	0.245	0.005	0.337	0.003	District	Share of households having confidence in the state government	IHDS
Share of elderly	0.090	0.002	0.111	0.001	District	Percentage of elderly population	IHDS
Share of SC, ST, OBC	0.718	0.005	0.713	0.003	District	Percentage of SC, ST, OBC population	IHDS
Share of Muslims	0.128	0.003	0.145	0.002	District	Percentage of Muslims	IHDS
Share of literate voters	0.568	0.003	0.637	0.002	District	Percentage of literate adults among adult population	IHDS

VARIABLES	2004-05 mean	2004-05 se	2011-12 mean	2011-12 se	Measurement level	Definition	Data source
Gini coefficient	0.343	0.002	0.338	0.001	District	Gini coefficient based on consumption exp. adj. for social pension benefits	IHDS
Head count ratio	0.442	0.004	0.232	0.003	District	Head count ratio based on consumption exp. adj. for social pension benefits	IHDS
Political competition	0.669	0.002	0.662	0.001	District	Political competition in the Lok Sabha constituency based on the Hirschman-Herfindahl concentration index	Election Commission
Participation in public meeting	0.296	0.003	0.253	0.002	District	Share of households participating in public meetings	IHDS
Share electrified	0.589	0.006	0.739	0.005	District	Share of households having electricity	IHDS
Share bureaucratic difficulties	0.070	0.002	0.064	0.001	District	Share of households having bureaucratic difficulties with ration card	IHDS
Share tax revenue	0.064	0.000	0.074	0.000	State	Ratio of real own tax revenue of the state (at 2004-05 prices) to its real gross state domestic product (at 2004-05 prices), indicator of state capacity	Reserve Bank of India
Judicial speed	0.370	0.004	0.305	0.005	State	Disposal rate as indicator of judicial speed or institutional efficiency	Reserve Bank
Coverage	0.100	0.002	0.215	0.001	State	Social pension coverage of age-wise eligible elderly	Reserve Bank
Number of observations	5015		7399				

4.D Qualitative research

Table 4.1: List of interviews conducted in Delhi in Spring 2016

Name	Designation	Date
Mr Ladu Kishore Swain	Member of Parliament, Aska, Odisha (Party: Biju Janata Dal)	16 March 2016
Mr Konda Vishewar Reddy	Member of Parliament, Chelvella, Telangana (Party: Telangana Rashtra Samiti)	21 March 2016
Mr Udit Raj	Member of Parliament, North West Delhi, Delhi (Party: Bharatiya Janata Party)	21 March 2016
Mr Jagdambika Pal	Member of Parliament, Domariyaganj, Uttar Pradesh (Party: Bharatiya Janata Party)	22 March 2016
Mr Nikhil Dey	Social Activist, Mazdoor Kisan Shakti Sangathan, Rajasthan	28 March 2016
Prof Arvind Panagariya	Vice-Chairman, National Institute for Transforming India (former Planning Commission), New Delhi	28 March 2016
Dr Ashok K. Jain	Adviser, Rural Development, National Institute for Transforming India (former Planning Commission), New Delhi	28 March 2016
Dr Rinku Murgai	Economist, World Bank, New Delhi	12 April 2016

4.E Defining tolerance bands for eligibility criteria

Though the eligibility cut-offs for age, income, and land possession are clearly defined and unambiguous in official documents of the seven analyzed states, their implementation in reality is problematic because many of the rural elderly may not provide documentary proof of their eligibility. This leaves some type of subjective "margin of error" in deciding who should be (in)eligible for pensions. For example, if someone is 59 years old (cut-off 60 years) and applies for old-age pension without any documentary proof of her age, there is a chance of her being included. In comparison with someone who is much younger than the cut-off age, this case is clearly not a gross violation of eligibility criteria. One way of distinguishing these two cases is to construct a band around eligibility cut-offs. It is obvious that we cannot find any statistical error band around some arbitrary number. However, we may find the standard error of an estimator of the corresponding distributional parameter. To incorporate this "margin of error" we construct a 95% confidence band around the cutoffs using the sampling distribution of the estimator of the corresponding percentile of the distribution. The steps to find the band are given below.

Age: We find the percentage of the population who are below 60 years (or 65 years depending on year and state). Let this be x percent. Therefore, our age cut-off is xth percentile of the age distribution. We now find standard error and 95% confidence band of the estimate of xth percentile. We do this separately for each state in two periods. If someone is above the upper limit of this band, she is considered as 'clearly eligible' (i.e., must be included) in terms of age. We follow the same method to find bands around income and land-holding criteria.

Destitute: The destitution criterion is not as objective as the age or BPL criteria. However, we know that pensions were available for 50% of the elderly below the Tendulkar poverty line. Therefore, we interpret the bottom-half of the poor as destitute. First, we convert nominal monthly per capita consumption expenditure (MPCE) to real using block specific poverty line deflators (Tendulkar poverty line). The consumption expenditure considered here is net of social pension receipts. Then we find the median of the real MPCE of the poor (Tendulkar). Finally, the standard error and 95% confidence band around the median are found separately for each state in two periods.

BPL: Below Poverty Line (BPL) cards are distributed based on a census carried out by the Government of India in 2002. This census assessed several socio-economic conditions of the poor households including asset holding, housing, clothing, sanitation, education, occupation, employment, and indebtedness and migration status. We first estimate a Probit model of BPL card holding status based on the above socio-economic conditions using IHDS survey data for the relevant year. This model is estimated separately for each state. We then find the cut-off for the positive outcome based on the mean of the propensity scores of the BPL card holders in each state separately. The standard error of the estimated mean is used to construct the 95% confidence band around the cut-off.

Since this is only an approximation, it may happen that an actual BPL card holder does not fall into this interval. To ensure that the band is not more restrictive than the original indicator, we consider both criteria jointly to define who is clearly eligible or ineligible: A person is considered as 'clearly eligible' (must be included) if he does hold a BPL card and has an asset-based propensity of holding a BPL card greater than the upper limit of the confidence band.

Persons are considered as wrongly excluded according to our measure allowing for the tolerance band if and only if they do not receive the pension while they are 'clearly eligible' according to all eligibility criteria of either the national or the relevant state scheme.

4.F Alternative transparency measures

This appendix first provides further details on the construction of transparency measures A and B, and then presents the results based on a replication of Tables 4.1 and 4.2 using these alternative transparency scores.

As explained in the text, Transparency A is based solely on the number of conditions through which eligibility is defined in each state and period. Age criteria are not taken into account as they are required everywhere and at all times. For the remainder, we have already defined four categories of frequently used criteria, namely destitution, income, land holding and BPL card. Within these, there can be different sub-clauses, namely different regulations for rural and urban areas, or for male and female individuals. In addition, some states use further criteria outside the four general categories, e.g. domicile requirements. When summing up the different clauses and sub-clauses, we get to an empirical maximum of four per state and year. To let the final transparency score start from 1 (lowest level of transparency) and to increase with lower levels of complexity, it is computed as:

$$\text{Transparency A}_{jt} = 5 - (\text{number of conditions})_{jt}, \forall \text{ state j and period t} \tag{4.3}$$

For example in Uttar Pradesh 2011-12 we have two types of conditions for BPL (see Appendix A), hence a count of 2 for the BPL category. There are no other conditions in any other categories. So the overall count is 2, and Transparency A is $5 - 2 = 3$.

Transparency B does not consider the number of conditions, but only their verifiability. The verifiability weight for each category of conditions are the same as used for the construction of Transparency C and explained in Section 4. Higher verifiability weight means more difficult to verify. These weights, W_i are: destitution=8 (most vague, most difficult to assess), income=4, land holding=2, and BPL card holding=1 (easiest to assess). When computing the transparency score, we consider that if one condition is vague, eligibility as a whole becomes vaguely defined and hence transparency is low. Transparency B is thus determined (inversely) by the criterion used that obtains the maximum weight:

$$Transparency\ B = 9 - \max_i \{W_i I_i\}$$

where $I_i = 1$ if criterion i is specified, 0 otherwise. Transparency B is the lowest (= 1) when destitution is specified in the list of all criteria, it is the highest (= 8) when BPL is the only criterion. For example in Karnataka 2004-05 income and BPL are used as criteria (see Appendix 1). Income has a verifiability weight of 4, while BPL has a weight of 1. Income is the least verifiable among the two. Hence the value of Transparency B is $9 - \max\{4, 1\} = 5$. Table 4.2 below compares the two complementary measures, both with each other and with the combined measure Transparency C explained in Section 4.

Table 4.2: Transparency scores by state and year

	Transparency A		Transparency B		Transparency C	
	2004-05	2011-12	2004-05	2011-12	2004-05	2011-12
Himachal Pradesh	2	1	1	5	14	21
Haryana	2	2	5	5	22	21
Uttar Pradesh	1	2	1	8	16	28
West Bengal	4	4	1	8	22	29
Madhya Pradesh	4	2	1	1	22	19
Odisha	4	1	1	1	22	13
Karnataka	3	3	5	5	25	25

The correlation between the different indexes is relatively low for Transparency A and B ($\rho_{A,B} = 0.05$) since they are based on different conceptual ideas. At the same time each of them is highly correlated with Transparency C since they contribute to the computation of the latter ($\rho_{A,C} = 0.54$, $\rho_{B,C} = 0.815$). Noticeably, the effect of the reforms in the late 2000s seems to be reflected in improved transparency only when looking at Transparency B. While they led to an improvement in the verifiability of the criteria (stronger focus on

BPL), the number of clauses and sub-clauses was often not reduced and even increased in several states.

The tables 4.3-4.6 below present the regression results using Transparency A and B rather than Transparency C (cf. Table 4.1 and 4.2), each time first with sharp eligibility criteria and then with the use of the tolerance band. With one exception, the effect of the transparency measure remains negative and significant throughout, i.e. no matter which dimension of transparency we consider. The exception is the case of Transparency A with band in the regression without any controls. Since this is the least reliable regression, this does not affect the general conclusion. However, it may be interesting to note that Transparency A is generally much less robust to changes in the set of controls than Transparency B or C.

Table 4.3: Transparency measure A and error wrongly excluded without band

	(1)	(2)	(3)	(4)	(5)
Year 2012	-0.292***	-0.310***	-0.181***	-0.205***	-0.192***
	(0.0205)	(0.0233)	(0.0343)	(0.0334)	(0.0299)
Transparency A	-0.0208**	-0.0819***	-0.0718***	-0.0806***	-0.155***
	(0.0069)	(0.0130)	(0.0130)	(0.0131)	(0.0145)
Adj. R-Squared	0.08	0.11	0.11	0.13	0.17
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.46	0.46	0.46	0.46	0.46
Between 0 and 1	1.00	1.00	1.00	1.00	1.00
Observations	12414	12414	12414	12412	12412

Dependent variable is wrong exclusion without tolerance band. Standard errors shown in parentheses are clustered at the district level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4: Transparency measure A and error wrongly excluded with band

	(1)	(2)	(3)	(4)	(5)
Year 2012	-0.313***	-0.326***	-0.193***	-0.212***	-0.184***
	(0.0200)	(0.0211)	(0.0347)	(0.0343)	(0.0327)
Transparency A	0.00182	-0.0508***	-0.0404**	-0.0456***	-0.128***
	(0.0074)	(0.0118)	(0.0119)	(0.0123)	(0.0122)
Adj. R-Squared	0.10	0.14	0.14	0.16	0.21
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.36	0.36	0.36	0.36	0.36
Between 0 and 1	1.00	1.00	1.00	0.99	0.99
Observations	12414	12414	12414	12412	12412

Dependent variable is wrong exclusion with tolerance band. Standard errors shown in parentheses are clustered at the district level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.5: Transparency measure B and error wrongly excluded without band

	(1)	(2)	(3)	(4)	(5)
Year 2012	-0.104***	-0.0485	-0.0650	0.0521	0.00412
	(0.0223)	(0.0244)	(0.0349)	(0.0352)	(0.0348)
Transparency B	-0.0458***	-0.0610***	-0.0621***	-0.0550***	-0.0575***
	(0.0050)	(0.0066)	(0.0066)	(0.0057)	(0.0057)
Adj. R-Squared	0.13	0.14	0.16	0.17	0.17
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.46	0.46	0.46	0.46	0.46
Between 0 and 1	1.00	1.00	1.00	1.00	1.00
Observations	12414	12414	12412	12412	12412

Dependent variable is wrong exclusion without tolerance band. Standard errors shown in parentheses are clustered at the district level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.6: Transparency measure B and error wrongly excluded with band

	(1)	(2)	(3)	(4)	(5)
Year 2012	-0.111***	-0.0908***	-0.0471	-0.0616	-0.0174
	(0.0246)	(0.0258)	(0.0309)	(0.0314)	(0.0303)
Transparency B	-0.0495***	-0.0560***	-0.0539***	-0.0546***	-0.0496***
	(0.0041)	(0.0065)	(0.0064)	(0.0062)	(0.0045)
Adj. R-Squared	0.16	0.17	0.17	0.19	0.21
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.36	0.36	0.36	0.36	0.36
Between 0 and 1	1.00	1.00	1.00	0.99	0.99
Observations	12414	12414	12414	12412	12412

Dependent variable is wrong exclusion with tolerance band. Standard errors shown in parentheses are clustered at the district level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.G Alternative regression model

Table 4.7: Logit model - transparency measure C and error wrongly excluded without band

	(1)	(2)	(3)	(4)	(5)
Wrongly excluded without band					
Year 2012	-0.797***	-0.756***	-0.543***	-0.639***	-0.435**
	(0.0795)	(0.0746)	(0.1244)	(0.1419)	(0.1397)
Transparency C	-0.0869***	-0.106***	-0.101***	-0.114***	-0.130***
	(0.0090)	(0.0148)	(0.0148)	(0.0145)	(0.0125)
PSeudo R-Squared	0.08	0.09	0.09	0.12	0.14
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.46	0.46	0.46	0.46	0.46
Observations	12414	12414	12414	12412	12412

Dependent variable is wrong exclusion without tolerance band. Marginal effects are shown. Standard errors shown in parentheses are clustered at the district level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.8: Logit model - transparency measure C and error wrongly excluded with band

	(1)	(2)	(3)	(4)	(5)
Wrongly excluded with band					
Year 2012	-0.944***	-1.009***	-0.743***	-0.827***	-0.542***
	(0.0924)	(0.0826)	(0.1354)	(0.1390)	(0.1504)
Transparency C	-0.0934***	-0.104***	-0.0979***	-0.109***	-0.130***
	(0.0087)	(0.0146)	(0.0145)	(0.0148)	(0.0113)
Pseudo R-Squared	0.10	0.12	0.12	0.15	0.18
State fixed effects	No	Yes	Yes	Yes	Yes
State coverage	No	No	Yes	Yes	Yes
Exogenous covariates	No	No	No	Yes	Yes
Endogenous covariates	No	No	No	No	Yes
Avg. predicted value	0.36	0.36	0.36	0.36	0.36
Observations	12414	12414	12414	12412	12412

Dependent variable is wrong exclusion with tolerance band. Marginal effects are shown.
Standard errors shown in parentheses are clustered at the district level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.H Consumption expenditure as alternative poverty indicator

Figure 4.9: Consumption quintiles of wrongly excluded

Source: IHDS I for 2004-05 and IHDS II for 2011-12.

5

Is Crowding Out of Private Support a Valid Concern?

5.1 Introduction

As resources for social protection schemes tend to be very limited, in most developing countries including India, social pensions benefits only mitigate, but do not eliminate old-age poverty, and elderly individuals are likely to continue depending on private support provided by family members. One aspect of this support is coresidence, assuming that other family members - and notably working age children - living in the household, will usually take some care of the elderly. This chapter therefore examines empirically how social pension receipt affects the living arrangements of elderly with their working age children. Coresidence is thereby considered as a relevant proxy for the provision of private support more generally.

This chapter contributes to the existing literature in the following ways. First, the effectiveness of social pensions in developing countries remains in general an under-researched topic. As the elderly poor differ in several ways from other target groups of cash transfers, what we know about the effectiveness of cash transfers in general cannot be directly applied to the effectiveness of social pensions for the elderly poor. Second and more importantly, we lack knowledge on potential constraints to the effectiveness of social pensions. The previous chapters have shown that we need to be concerned about the targeting performance. The potential behavioral response of family members, however has rarely been examined yet. In addition, the focus of extant studies on coresidence is on developed countries like the US (Costa 1997) or on upper middle income countries like South Africa (Hamoudi & Thomas 2014; Edmonds et al. 2005) or Brazil (Lloyd-Sherlock 2006). In developing countries, reactions may be different among other things because the social pensions are much smaller, and traditional family structures are still more important. In addition, the question of how family support reacts to social pension receipt will become more and more important for developing countries that face accelerating demographic change.

Directly related to this chapter, existing studies have examined the effect of an expansion in pension coverage or pension amounts on living arrangements of the elderly. Costa's 1997 study for the US examines the factors explaining a rise in single-elderly households and shows that the expansion of pensions enabled elderly to afford separate living arrangements. The ability to afford individual living arrangements in old-age is in this context considered as an improvement in the quality of life as it enables elderly to have greater control over their lives and resources. It is questionable that this positive interpretation of individual lifestyle can be also applied to the developing country context and to more collectivistic cultures like the Indian one. Recently and for a very different context, Chen (2017) shows similarly that social pension income reduces inter-generational coresidence and increases the consumption of services (haircut and repairs) by the elderly in China. For the case of South Africa, Edmonds et al. (2005) do not find any change in the independence of elderly but they do find that the household composition changes with those having a comparative advantage of working away from home leaving the household. Hamoudi & Thomas (2014) show for the same context that the expansion of the South African social pension resulted in beneficiaries living with those adults who have lower human capital.

While China is nowadays categorized as upper middle income country, the context studied by Chen (2017) is closest to the context of developing countries. However, more importantly, the examined social pension scheme in China covers all elderly independent of their socio-economic status and it remains unclear whether the described effects would have been also observed if the scheme focused on the elderly poor in the population as most social pension schemes around the world do.

The Indian context is relevant for this research question because of the following features: First, as mentioned in the previous chapters, India is a developing country with rapidly progressing demographic change (James 2011; Murthi et al. 1995). Second, despite India's impressive economic growth over the past two and a half decades, more than 90 percent of the Indian labor force still works in the informal sector without any access to formal pension schemes (e.g. Sastry 2004). Third, social norms regarding coresidence with adult children are very strong, and especially the tradition of patrilocality (implying that newly married couples move into the house of the groom's family) continues to be very prevalent (Murthi et al. 1995). Fourth, typical for a developing country, targeting problems and implementation issues prevail in the social pension scheme and may weaken the link between eligibility rules and social pension receipt as shown in detail in the previous chapters. Finally, and in my view most importantly, the social pension amount is very modest on average. In most states it is much lower than the poverty line and compared to other developing countries, the Indian poverty line has been criticized by various scholars for being extremely low (Drèze & Khera 2017). In addition to the low amounts of social pension benefits, the timing of social pension receipt is very uncertain in several Indian states. Beneficiaries have reported delays of payment of several months (Drèze & Khera 2017). Hence, especially in regions with low and irregular payments of benefits, if social pension receipt leads to reduced coresidence with own working age children, this may imply that the well-being of the elderly does not improve with the social pension receipt but instead deteriorates as elderly receive low and irregular payments from the government but lack the private support from their working age children.

Methodologically, I contribute to the existing literature by using panel data methods to account for individual level time-invariant heterogeneity and an instrumental variable approach to address endogeneity concerns, i.e. notably reverse causality. As coresidence with adult children might have been officially or unofficially considered for the selection of beneficiaries, social pension receipt does not only affect coresidence but coresidence can also affect social pension receipt. In some states, living with working age children was officially used as eligibility criterion. Alternatively, local government officials in charge of selecting beneficiaries perceive applicants who live with their working age children differently than those who do not. Finally, working age children can support their parents in applying for social pensions. If this reverse causality exists, estimates that do not account for this endogeneity concern are expected to be biased.

As in the previous chapters, I use the two rounds of the India Human Development Survey (IHDS) to study the living arrangements of a panel of elderly household members in 2004-05 and 2011-12. Considering the reforms of India's social pension scheme in terms of coverage and social pension amount over this period, I am able to compare the living arrangements of the elderly before and after the relevant reforms in 2006 and 2007 to identify the differential effect of social pension receipt if any and to apply instrumental variable estimation techniques that address the described concern of reverse causality.

The remainder of this chapter is structured as follows: Section 5.2 describes the underlying theoretical considerations and the existing literature. Section 5.3 presents the data and explains the empirical methodology; Section 5.4 describes the empirical results. Section 5.5 provides concluding remarks.

5.2 Theoretical Considerations and Literature

From a theoretical perspective, it is unclear how living arrangements with elderly may be shaped in response to the social pension receipt. On the one hand, non-elderly household members might benefit from the social pension income due to income pooling, which in turn may induce them to continue living with the elderly beneficiary (e.g. Case & Deaton 1998). On the other hand, the additional income may be seen as sufficient for satisfying basic needs while living without working age children and encourage other household members to leave the household to pursue better working opportunities or to live independently elsewhere (e.g. Edmonds et al. 2005).

Indirectly related to coresidence, there is a larger body of literature on the impact of social pensions on inter-generational transfers. The receipt of pension benefits enables the elderly person to engage in inter-generational transfers from the elderly recipient to other household members. This has been shown for South Africa (Case & Deaton 1998; Duflo 2000), Brazil (Lloyd-Sherlock 2006) and China (Mu & Du 2015). While this sharing of resources could motivate individuals to continue to live with the elderly person, several papers have shown that coresidence might actually become less frequent when elderly members receive pension benefits (e.g., see Chen (2017) for China, Costa (1997) and Ruggles (2007) for the US and Posel et al. (2006) for South Africa). Further Edmonds et al. (2005) and Hamoudi & Thomas (2014) show that selective sorting takes place in households that receive social pension benefits. While unproductive members such as child-bearing women continue to live with the elderly beneficiary, other adults in the prime working age leave the household to take up employment opportunities.

A reduction of private support could be particularly problematic in a context where social pension amounts are low and irregular. If an elderly person starts receiving social pension benefits but loses potentially even more valuable private support from family members, the elderly person may be worse off after obtaining access to social pensions and the old-age poverty reduction objective envisioned by the government might not be achieved.

For the Indian context or even poorer countries, e.g. in Africa, I am only aware of anecdotal evidence pointing in both theoretical directions: Elderly have reported in interviews with civil society organizations that they have experienced behavioral reactions of both extremes. Either they felt much more valued by other family members because of the additional household income and the quality of coresidence improved, or they were left alone because other family members did not feel the moral obligation any more to care for them (HelpAge International 2009).

5.3 Data and Methodology

5.3.1 The India Human Development Survey

As in previous chapters, the IHDS is the main data source for this analysis. Its main characteristics have been explained earlier, but are briefly summarized again. The IHDS was conducted by the National Council of Applied Economic Research and the University of Maryland (Desai et al. 2015; Desai & Vanneman 2015). The nationally representative panel includes 41,554 households (215,753 individuals) in 1503 villages and 971 urban neighborhoods across India based on a stratified, multistage sampling procedure in 2004-05 and re-interviewed households in 2011-12. The IHDS includes a broad range of economic development question modules regarding demographics, health, public welfare programs, agriculture, employment, gender relations, education, social networks and institutions, etc. at both individual and household level (Desai et al. 2015).

In this chapter, the dependent variable is coresidence with own working age children coded 1 if the elderly lives with own children who are at least 16 years old and 0 otherwise. The independent variable of interest is social pension receipt as a dummy variable.[1] I control for a number of variables measured at the individual level, at the household level and at the village level as explained in more detail below. The complete list of variables and their definitions is shown in Table 5.9 in the Appendix.

5.3.2 Empirical methodology

The empirical analysis uses a sample of individuals that is likely to be affected by the expansion of social pension coverage in between 2004-05 and 2011-12. I restrict the sample in terms of age, wealth and marital status. In terms of age, I include all elderly who have a relevant chance to receive a social pension in the second period, but who are not supposed to receive a social pension in the first period. For simplicity, I include all elderly who are in between ten years and one year younger than the eligibility age in 2004-05. This implies that elderly who are as old as the eligibility age or older in 2004-05 are not included in the sample of analysis as they are not going to cross the age-wise eligibility cutoff. In terms of wealth, the social pension is irrelevant for individuals from

1 In theory, I could also examine how the pension amount affects coresidence with working age children. However, the instrumental variable estimation explained in more detail below is not suitable to examine the effect of social pension amounts on coresidence and I therefore focus on social pension receipt.

rich households, I therefore exclude individuals from households with asset ownership in the top quartile. Finally, I exclude those elderly who are never married singles and those elderly who live as servants in households, as their coresidence with working age children cannot be plausibly affected. To account for individual level heterogeneity, the empirical analysis is based on a balanced sample of 4169 elderly individuals who have been surveyed in both 2004-05 and 2011-12.

I proceed in two steps: First using linear probability models with individual fixed effects and second, an instrumental variable approach, I study the same elderly over 2004-12 to identify changes in their coresidence with own children in the time period of relevant social pension reforms. I examine whether all children, all sons or all daughters in working age have left the household between 2004-05 and 2011-12 in three separate specifications. Since I use panel data for two time periods, first difference estimates would yield the same results. Apart from the individual fixed effects that account for time-invariant individual level heterogeneity, I also control for time-varying covariates at the individual, household and village level.

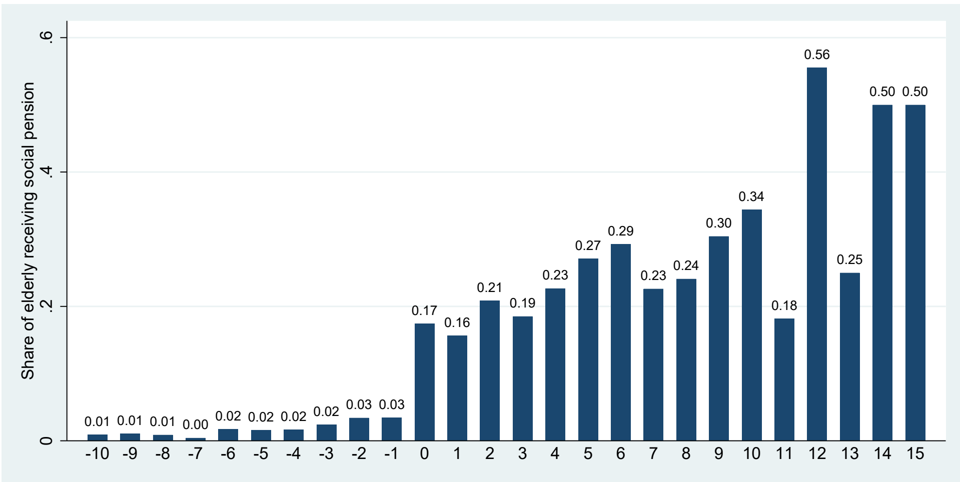
While the linear probability model with individual fixed effects and relevant time-varying covariates minimizes the potential omitted variable bias by accounting for individual level heterogeneity, there may still remain some issues related to a potential reverse causality between coresidence and social pensions. As mentioned above, social pensions may not only affect coresidence with own children but coresidence with own children may also affect social pension receipt. This is obviously the case when coresidence is an official criterion for exclusion from pension benefits. But there are factors apart from eligibility which may also affect the direction of causality. For instance, local government officials in charge of selecting beneficiaries might not perceive the need for a social pension of an elderly person living with children or elderly might rely on children's help for the application procedures.

I use instrumental variable estimations to remove these concerns about a potentially reversed impact of coresidence on social pension receipt. Using an instrumental variable indicating whether the elderly person is older than the local age cut off based on administrative rules fixed by each state government, I estimate instrumental variable regressions with individual fixed effects in three specifications focusing on living with working age children, living with working age sons and living with working age daughters. The idea to use the age-cutoff to predict social pension receipt has been previously used in other studies (Chen 2017; Duflo 2000; Edmonds et al. 2005).

Despite of the immense targeting problems in the implementation of social pensions in

India (see Chapter 3 and 4), Figure 5.1 below illustrates that the age cutoff is relevant and approximately followed in practice. Displaying the difference in years between the age of the elderly person and the state-specific eligibility age for social pensions, we clearly see that the share of elderly receiving the social pension shifts up sharply when elderly reach the eligibility age. That is, elderly individuals who are older than the eligibility age are more likely to receive the social pension than individuals who are younger than the eligibility age. Hence, based on these descriptive statistics the instrument indicating whether an individual is older than the locally relevant age cutoff seems to be relevant to predict social pension receipt. This will be further shown with the first-stage regressions of the instrumental variable estimation.

Figure 5.1: Share of social pension recipients by distance to age cutoff



The x-axis shows the distance to the age cutoff with negative (positive) numbers indicating how many years the individual is younger (older) than the eligibility age with 0 indicating that the individual is as old as the eligibility age.
Source: Author's illustration based on IHDS-I for 2004-05 and IHDS-II for 2011-12.

One might be rather concerned here about the exclusion restriction. Age can directly affect coresidence with own children. To make sure that the exclusion restriction is also plausibly fulfilled, I control for the age and of the individual and only use the switch between being younger than the eligibility age and being older than the eligibility age as a predictor of social pension receipt. I also control for indicators of physical weakness and working status that could be directly affected by being older than the cutoff and also can play a relevant role for coresidence decisions. Additionally, I further use an alternative instrument to corroborate my findings namely village level promotion of the social pension scheme interacted with the age-wise eligibility for social pensions.

To address potential concerns regarding weak instruments, I follow Angrist & Krueger (2001) who suggest to examine the reduced form i.e. the regression of the dependent variable on the instrument and the other exogeneous covariates. ”These estimates are unbiased, even if the instruments are weak.” (Angrist & Krueger 2001, p.79). for instance, if the IV estimates appear to be inflated, one can use the unbiased reduced form estimates to assess the sign and size of the coefficient simply by rescaling the reduced form estimates with the coefficient from the first stage.

After presenting the main results, I discuss the validity of the empirical methodology and explain how the relevant conditions for instrumental variable estimation are fulfilled. I further show that the results are not driven by individual states and remain roughly the same when I exclude one state after another.

Finally, to understand whether certain sub-groups among the elderly are particularly prone to being exposed to changes in the living arrangement, I use interaction terms to test whether the estimated effects are stronger or weaker for elderly suffering from major morbidities, elderly suffering from difficulties with activities of daily living, elderly in rural areas and elderly who have more decision-making power.

5.4 Results

5.4.1 Descriptive statistics

The summary statistics for the sample of analysis are presented in Table 5.1. In 2004-05, 80 percent of the elderly live with working age children, 73 percent with working age sons and 25 percent with working age daughters. In 2011-12 these percentages have reduced to 69 percent, 63 percent and 17 percent respectively. As I focus on own working age children, these percentages reflect the patrilocality tradition in India. After getting married, bride and groom move into the household of the groom, so that elderly traditionally tend to live with their sons and their daughters in law. Corresponding to the selected age group of individuals in the sample with all individuals being younger than the eligibility age in 2004-05, 0 percent are eligible by age in 2004-05 and 80 percent in 2011-12. 1 percent of the elderly receives social pensions in 2004-05 and 19 percent in 2011-12. Similarly, 56 percent of the sample are women and the average age increases from 54 to 61 years from 2004-05 to 2011-12. Corresponding to the increasing age of the individuals in the sample, the share of individuals working reduces from 77 percent to 55 percent. Literacy rates remain stable at 33 and 32 percent and the share of elderly being the head of household slightly increases from 49 to 54 percent. The physical frailty linked to aging is clearly reflected in the data. Such as, on average elderly individuals suffer from 0.13 major morbidities in 2004-05 and from 0.34 major morbidities in 2011-12. Similarly, the average number of difficulties with activities of daily living (ADL) that elderly suffer from increases from 0.11 to 0.53. These are the covariates at the individual level.

Covariates at the household level develop as expected: Number of assets owned increases, size of land holding decreases, house ownership stays stable, BPL card holding has increased over time and the maximum education level in the household stayed stable. About 15 to 16 percent of the elderly in the sample live in urban areas. As a proxy for liberal attitudes and modernization, I include a dummy indicating whether women in the household use contraceptives. This is a behavior that significantly increased over time.

Covariates at the village level reflect transaction costs related to the application for social pensions and general measures of economic development and village-level cooperation. The distance to the next town slightly decreased over time, the share of electrified households in the village increased significantly and the share of households reporting that life in the village is peaceful or that households work together to solve local problems (collaboration rate) also increased in between the two survey rounds in 2004-05 and 2011-12.

Table 5.1: Summary statistics

	2005				2012			
	mean	sd	min	max	mean	sd	min	max
Lives with child	0.80	0.40	0	1	0.69	0.46	0	1
Lives with son	0.73	0.44	0	1	0.63	0.48	0	1
Lives with daughter	0.25	0.43	0	1	0.17	0.38	0	1
Social pension	0.01	0.09	0	1	0.19	0.39	0	1
Eligible by age	0.00	0.00	0	0	0.80	0.40	0	1
Female	0.56	0.50	0	1	0.56	0.50	0	1
Age	54.13	3.04	45	59	61.40	4.24	45	75
Working	0.77	0.42	0	1	0.55	0.50	0	1
Literate	0.33	0.47	0	1	0.32	0.47	0	1
Head of household	0.49	0.50	0	1	0.54	0.50	0	1
Widowed	0.15	0.35	0	1	0.25	0.43	0	1
Married	0.85	0.36	0	1	0.74	0.44	0	1
N of major morbidities	0.13	0.40	0	5	0.34	0.66	0	5
N of ADL difficulties	0.11	0.64	0	7	0.53	1.26	0	7
Household assets	9.19	4.07	0	18	11.48	4.39	0	18
Land holding	2.52	5.65	0	200	1.82	3.70	0	100
Own house	0.97	0.17	0	1	0.97	0.18	0	1
BPL card	0.45	0.50	0	1	0.52	0.50	0	1
Max education	6.52	4.80	0	15	6.62	4.85	0	15
Urban	0.15	0.36	0	1	0.16	0.37	0	1
Contraceptives use	0.24	0.43	0	1	0.38	0.49	0	1
Social organization	0.37	0.48	0	1	0.36	0.48	0	1
Public meeting	0.33	0.47	0	1	0.33	0.47	0	1
Government connection	0.13	0.34	0	1	0.30	0.46	0	1
Permanent job	0.08	0.28	0	1	0.10	0.30	0	1
Distance to town	12.03	11.34	0	85	11.91	11.91	0	110
Electrification rate	0.67	0.32	0	1	0.83	0.24	0	1
Peaceful village rate	0.53	0.36	0	1	0.58	0.34	0	1
Collaboration rate	0.58	0.32	0	1	0.73	0.26	0	1
Observations	4169				4169			

Individuals selected into the sample of analysis are between 10 years and 1 year younger than the local eligibility age in 2004-05, not unmarried singles and do not belong to a household with asset ownership in the top-quartile.

5.4.2 Regression results

I begin with the results from the linear probability model with individual fixed effects before discussing the two-stage least squares results that take into account the potential problem of endogeneity of the explanatory variable of interest.

In Table 5.2, I present the results from three specifications regressing coresidence with working age children, with working age sons and with working age daughters on social pension receipt. The results suggest that receiving a social pension is associated with a 5.2 percentage points reduction in the likelihood of living with own working age sons (significant at the 5 percent level). The coefficient for living with own working age children is also negative but insignificant and the coefficient for living with working age daughters is positive but much smaller and insignificant. The linear probability model suffers from the typical problem of predictions being outside the [0;1] range. This is particularly a concern in the first specification where 16 percent of the predictions are smaller than 0 or greater than 1. For the second specification that shows a significant relationship between social pension receipt and coresidence with own working age sons, the share of predictions outside the [0;1] range is 9 percent. The significant effect of 5.2 percentage points is also economically significant considering the average predicted value of 0.69.

Table 5.2: Linear probability model

	(1) With child	(2) With son	(3) With daughter
Social pension	-0.042	-0.052**	0.014
	(0.026)	(0.026)	(0.022)
Individual controls	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
Village controls	Yes	Yes	Yes
Observations	8338	8338	8338
Number of id	4169	4169	4169

Standard errors in parentheses

All specifications include individual and time fixed effects, as well as individual, household and village controls.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As explained above the regressions with individual fixed effects and relevant control variables mitigate the omitted variable bias related to time-invariant individual level heterogeneity but do not address the concern of reverse causality i.e. that the coresidence status of the elderly might also affect the likelihood of receiving a social pension. Therefore, I proceed with the instrumental variable estimations using two-stage least squares estimation.

To show the relevance of the chosen instrument i.e. being older than the eligibility age for the receipt of social pensions, I present first the first-stage of the instrumental variable estimation. Being older than the eligibility age is positively associated with a 14.3 percentage points higher likelihood of receiving social pensions significant at the 1 percent level. The F-statistic for the first stage of 99.81 indicates that being eligible by age is a sufficiently strong predictor of receiving social pensions even after controlling for age and all the other covariates described above. This F-test is used to address the concern that the instrument might be only weakly correlated with the endogenous variable of interest. The null hypothesis is that instrument is too weakly correlated with the endogeneous regressor causing a bias which is unacceptably large. With F-statistics being larger than the critical cutoff of 16.38, the null hypothesis is rejected and the IV estimates do not seem to suffer from a weak instrument problem (Newton et al. 2010).

Table 5.3: First stage of instrumental variable estimation

	(1) Social pension receipt
Eligible by age	0.143***
	(0.014)
F-stat	99.81
Individual controls	Yes
Household controls	Yes
Village controls	Yes
Observations	8338
Number of id	4169

Standard errors in parentheses

Specification includes individual and time fixed effects, as well as individual, household and village controls. Dependent variable of the second stage is living with working age children, sons or daughters.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results from the IV estimations with individual fixed effects and the full set of control variables indicate large negative and significant effects of social pension receipt on the likelihood to live with own working age children of 72 percentage points and to live with working age sons of 82 percentage points. Similar to the original fixed effects regressions, the effect for working age daughters is insignificant. Including age squared does not change the results but inflates the estimated coefficients even more.

Table 5.4: Instrumental variable estimation - coresidence

	(1) Living with children	(2) Living with sons	(3) Living with daughters
Social pension	-0.722***	-0.817***	-0.098
	(0.188)	(0.183)	(0.198)
Individual controls	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
Village controls	Yes	Yes	Yes
Observations	8338	8338	8338
Number of id	4169	4169	4169

Standard errors in parentheses

All specifications include individual and time fixed effects, as well as individual, household and village controls.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As the results from the instrumental variable estimations appear to be inflated, I examine the reduced form estimates (following Angrist & Krueger (2001)). I regress coresidence with working age children, with working age sons and with working age daughters on the instrument being eligible by age and all previously described covariates and individual fixed effects. The results from the reduced form estimation confirm the negative effects of social pension receipt on coresidence with working age children and working age sons with coefficients ranging from -0.06 to -0.08 (significant at the 1 percent level). Re-scaling these reduced form estimates by the coefficient of the first stage estimation of 0.14, the estimated effect size reduces to a 41 percentage points' reduction in the likelihood of living with working age children and 57 percentage points' reduction in the likelihood of living with working age sons.

To check the robustness of the results, I use an alternative external source of variation provided by IHDS interacted with being older than the eligibility age cutoff. This allows me to construct an alternative instrument that predicts social pensions receipt but not coresidence wih working age children. I use information about the village-level promotion

Table 5.5: Reduced form estimates

	(1) Living with children	(2) Living with sons	(3) Living with daughters
Eligible by age	-0.059***	-0.081***	-0.001
	(0.018)	(0.019)	(0.019)
Individual controls	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
Village controls	Yes	Yes	Yes
Observations	8338	8338	8338
Number of id	4169	4169	4169

Standard errors in parentheses

All specifications include individual and time fixed effects, as well as individual, household and village controls.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

of the social pension. Apart from the household survey, IHDS also includes a village survey in which a knowledgeable respondent from the village is asked whether social transfer schemes including the National Old Age Pension Scheme were promoted in the village. The idea here is that being older than the eligibility age cutoff and living in a village where the social pension scheme has been promoted increases the chances of receiving the social pension. Accounting for time-varying variables at the household and village level as well as including individual fixed effects makes it plausible that the instrument, as an interaction between village-level promotion and being older than the age cutoff, influences coresidence only through the pension receipt and not directly.

The results from the estimations with the alternative instrument confirm the negative effect of receiving social pensions. Elderly who receive social pensions are 46 percentage points less likely to live with their working age children (significant at the 5 percent level) and 69 percentage points less likely to live with their working age sons (significant at the 1 percent level). The reduced form estimates confirm the results with coefficients of -0.04 and -0.06 (both significant at the 1 percent level). Re-scaling the estimates from the reduced form by the coefficient from the first stage suggests a negative effect of social pension receipt on coresidence with working age children of 44 percentage points and on coresidence with working age sons of 60 percentage points. These results are close to the results from the reduced form estimates with the original instrument. However, with a first-stage F-value of 47.90 the instrument is weaker than just using the eligibility cutoff as an instrument.

Table 5.6: First stage of instrumental variable estimation

	(1) Social pension receipt
Pension promoted X eligible by age	0.100***
	(0.014)
1st stage F-stat	47.90
Individual controls	Yes
Household controls	Yes
Village controls	Yes
Observations	8124
Number of id	4062

Standard errors in parentheses

Specification includes individual and time fixed effects, as well as individual, household and village controls. Dependent variable of the second stage is living with working age children, sons or daughters.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.7: Instrumental variable estimation - alternative instrument

	(1) Living with children	(2) Living with sons	(3) Living with daughters
Social pension	-0.456**	-0.691***	0.012
	(0.215)	(0.214)	(0.215)
Individual controls	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
Village controls	Yes	Yes	Yes
Observations	8124	8124	8124
Number of id	4062	4062	4062

Standard errors in parentheses

All specifications include individual and time fixed effects, as well as individual, household and village controls.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.8: Reduced form estimation - alternative instrument

	(1) With child	(2) With son	(3) With daughter
Pension promoted X eligible by age	-0.044***	-0.060***	-0.005
	(0.014)	(0.015)	(0.015)
Individual controls	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
Village controls	Yes	Yes	Yes
Observations	8124	8124	8124
Number of id	4062	4062	4062

Standard errors in parentheses

All specifications include individual and time fixed effects, as well as individual, household and village controls.

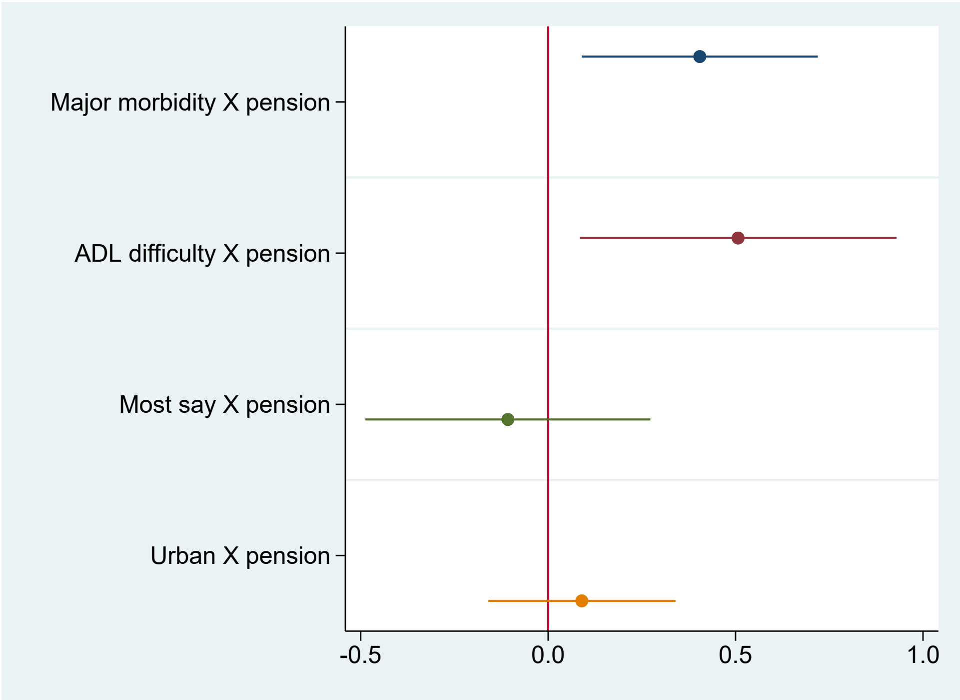
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.4.3 Heterogeneity analysis

To understand which elderly among the beneficiaries are most likely to experience the reduction in coresidence with their adult children, I proceed to examine potential heterogeneous effects. Do we observe that the estimated effects are different for physically weak elderly who suffer from a major morbidity or face difficulties with activities of daily living? Are the effects of social pension receipt on coresidence different for elderly who have decision-making power in their households or different for those who already live in urban areas?

As shown in Figure 5.2, the negative effect is significantly smaller for physically weak individuals who either suffer from a major morbidity or have difficulties with at least one activity of daily living. There are no differential effects for elderly who have decision-making power in their households or elderly who live in urban areas. These results imply that, at least to some extent, decisions on coresiding with the elderly person take into account the physical abilities of the elderly person to take care of herself.

Figure 5.2: Heterogeneity analysis



The presented coefficients are from interactions of the independent variable of interest social pension receipt with the stated covariate. The confidence intervals show significance at the 10 percent level but the differential effects of social pension receipt for individuals who suffer from a major morbidity and individuals who have difficulties with activities of daily living are both significant at the 5 percent level. Source: Author's illustration based on IHDS-I for 2004-05 and IHDS-II for 2011-12.

5.4.4 Validity and robustness of empirical results

Given the endogeneity of social pension receipt, the findings from the instrumental variable estimations are the main results of this chapter. To examine the validity of the empirical strategy, I proceed by discussing the underlying assumptions and testing the robustness of the results. First, to satisfy the relevance assumption, the instrument has to be a relevant predictor of social pension receipt. With F-values of 99.81 and 47.90 being much higher than the critical value of 16.38, the first stage regressions presented in Table 5.3 and Table 5.6 show that both instruments (1) being older than the eligibility age and (2) village level promotion interacted with age-wise eligibility are strong predictors of social pension receipt in terms of coefficient size and significance. The second requirement for instrumental variable estimation is that it must satisfy the exclusion restriction. This means that the instrumental variable should have no partial effect on the dependent variable after controlling for the independent endogenous variable of interest, covariates and omitted variables. Since this assumption considers the error term i.e. unobserved and omitted factors, by definition, it cannot be tested and only theoretically justified.[2]

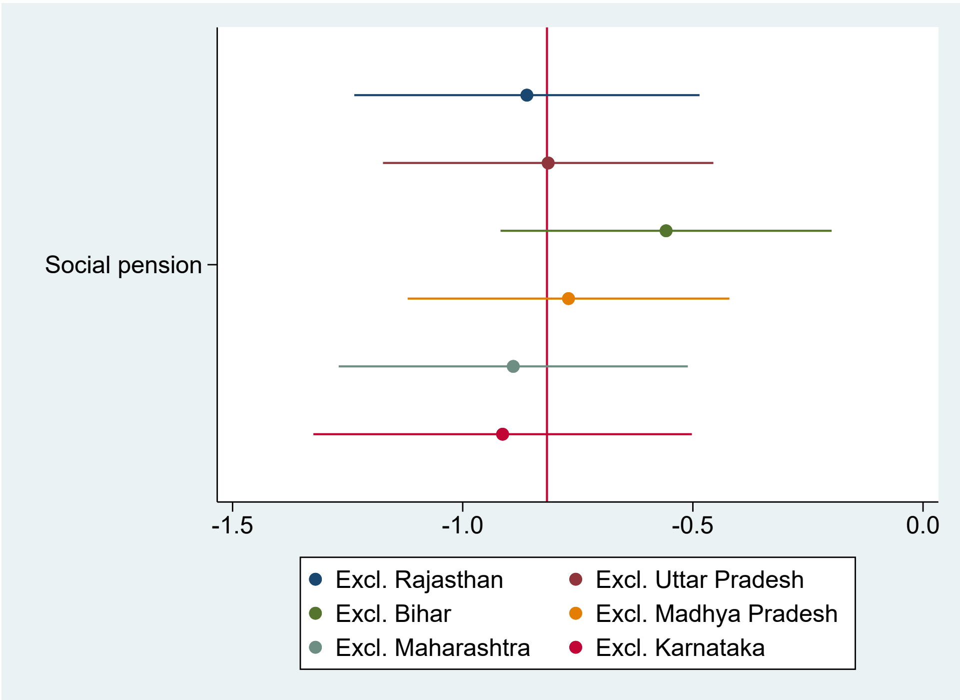
In the context of this analysis, it is obvious that living with working age children is influenced by the age of the elderly person. While at first sight, this appears to be a strong threat to the identification strategy, it is important to note that the direct effect of age on coresidence is already accounted for by including age as covariate in the regression model. Controlling for the age of the elderly person thereby addresses that continuous changes in age affect the likelihood of living with working age children. The instrument hence only exploits the fact that there is a cutoff between those who are younger than the eligibility age and those who are older. As shown above, the eligibility age is roughly followed in practice and individuals who are older than the eligibility age certainly more likely to receive the social pension than those who are younger than the eligibility age. Since the social pension targets informal sector workers who are not entitled to receive a formal sector pension which could start at the same cutoff age, there are no other relevant changes at the cutoff that could directly affect coresidence with working age children. The validity of this argument is strengthened further by the fact that the eligibility age changed in many states in between 2004-05 and 2011-12 (see Table 3.7 in the Appendix for state level eligibility ages).

I now examine whether the results are driven by one of the Indian states. Since state governments are responsible for the implementation of social pensions, this is indeed a

2 Even if after controlling for all the mentioned covariates, being older than the eligibility age would have a positive effect on coresidence, this would lead to an attenuation bias.

potential concern for the interpretation of the results. As shown below, this is not the case. When I leave out any of the major Indian states, the results continue to be stable and similar in size as visualized in Figure 5.3. The red line indicates the previously estimated point estimate from the full sample including all Indian states. None of the visualized coefficients is significantly different.

Figure 5.3: Sensitivity of results to included states



The visualized coefficients are from estimations that exclude one of the six indicated states which represent a major share of the sample of analysis.
Source: Author's illustration based on IHDS-I for 2004-05 and IHDS-II for 2011-12.

5.5 Conclusion

Overall, this chapter has shown the importance of taking into account potential unintended behavioral responses to understand the effectiveness of social pensions. The poverty-reducing impact is likely to be constrained if elderly who receive the social pension receive less private support from other family members. One potential approach to proxy this is to examine coresidence with working age children. The empirical findings support the concern that public support crowds out private support through a reduction in coresidence with working age sons.

These presented findings have relevant implications for the design and reform of social pension schemes in India. Based on these behavioral responses of other household members to the social pension receipt, future reforms of social pensions in the Indian context need to take into account potential reactions by other income-generating household members (most importantly own sons) affecting the overall well-being of the elderly person and eventually, the poverty-reducing impact of social pensions.

This empirical analysis is not without limitations and there are several questions that remain unanswered for future research. A major limitation is that coresidence with children is a rough proxy for private support. I am only able to observe whether elderly continue living with their children but I am unable to measure changes in actual support provided by their children. More detailed data on private support will be essential to examine how actual support is affected by social pension receipt.

Appendix

Table 5.9: List of variables

Variable	**Definition**
Lives with child	Dummy variable equal to 1 if individual lives with own working age children, 0 otherwise
Lives with son	Dummy variable equal to 1 if individual lives with own working age son, 0 otherwise
Lives with daughter	Dummy variable equal to 1 if individual lives with own working age daughter, 0 otherwise
Social pension	Dummy variable equal to 1 if individual receives social pension, 0 otherwise
Eligible by age	Dummy variable equal to 1 if individual is older than local eligibility age, 0 otherwise
Female	Dummy variable equal to 1 if individual is female, 0 otherwise
Age	Age of individual in years
Working	Dummy variable equal to 1 if individual works more than 240 hours per year, 0 otherwise
Literate	Dummy variable equal to 1 if the individual is literate, 0 otherwise
Head of household	Dummy variable equal to 1 if individual is head of household, 0 otherwise
Widowed	Dummy variable equal to 1 if the individual is widowed, 0 otherwise
Married	Dummy variable equal to 1 if the individual is married, 0 otherwise
N of morbidities	Number of major morbidities
N of ADL difficulties	Number of difficulties with activities of daily living
Most say	Indicator for elderly's say in household decisions coded as 1 if elderly male has most say regarding purchase of expensive items or if elderly female has most say regaring cooking
Household assets	Asset index for number of assets owned by household from 0 to 30
Land holding	Size of owned land 30

Own house	Dummy equal to 1 if household owns the house, 0 otherwise
BPL card	Dummy variable equal to 1 if individual is entitled to benefits through the ration card (either BPL or Antyodaya), 0 otherwise
Max education	Years of schooling completed by the most educated household member
Urban	Dummy variable equal to 1 if household lives in urban areas, 0 otherwise
Contraceptives	Dummy variable equal to 1 if women in the household use contraceptives, 0 otherwise
Social organization	Dummy variable equal to 1 if anybody in the household is a member of a social organization, 0 otherwise
Public meeting	Dummy variable equal to 1 if somebody from the household or close to the household is a local government official, 0 otherwise
Government connection	Dummy variable equal to 1 if somebody from the household or close to the household is a local government official, 0 otherwise
Permanent job	Dummy variable equal to 1 if anybody in the household has a permanent job, 0 otherwise
Distance town	Village's distance to the next town in kilometers, equal to 0 if urban area.
Electrification rate	Share of electrified households in the village
Peaceful village rate	Share of households reporting that village is peaceful
Collaboration rate	Share of households reporting that households collaborate to solve a problem

6

Conclusion

While it has been well established in the literature that in developing countries the effectiveness of social transfers in reducing poverty tends to be constrained, existing research has not devoted much attention to the factors constraining the effectiveness. This dissertation addresses this knowledge gap in two dimensions. I examine the targeting performance of social pensions and analyze potential unintended behavioral effects.

Mistargeting of social transfers aimed at mitigating poverty can be quantified in two ways. They are mistargeted if they do not reach the poor; and as most social transfers use eligibility rules for the selection of beneficiaries, they are also mistargeted if they do not reach those individuals or households who are officially eligible to receive the benefits. If targeted individuals do not receive the benefits and non-targeted individuals benefit from the scheme, the poverty-reducing impact is likely to be constrained and scarce resources are wasted. Further, unintended behavioral effects such as the crowding out of private support can reduce the effectiveness of social transfers in reducing poverty. I empirically examine both potential constraints in the context of social pensions in India using the India Human Development Survey as the main data source.

After having provided the relevant background information in Chapter 1 and Chapter 2, Chapter 3 examines the targeting performance and the relevant factors for access to social pensions. I first show descriptively that during a time-period of important social pension reforms, the targeting performance in terms of reaching the elderly poor overall improved. However, both errors of targeting continue to be very high. More than 70 percent of the elderly poor do not receive social pensions after the reforms and more than 40 percent of the beneficiaries are either younger than the eligibility age or non-poor. There is an urgent need to reconsider the targeting of social pension benefits in India due to the obvious difficulties in identifying elderly poor. As intended by the reforms, BPL card holding has become the most important determinant for access to social pensions. However, BPL cards themselves are in general too weakly allocated to the poor to facilitate effective targeting of social pensions. Further, having a personal connection to the local government, as a clearly illegitimate factor, facilitates access to social pensions for individuals from non-poor households.

Chapter 4 (based on a co-authored study) focuses on mistargeting in official terms. We examine whether making eligibility rules for targeting more transparent could be an effective measure to reduce official targeting errors. Previous studies that examined how transparency can improve the implementation of social transfers focused primarily on transparent delivery mechanisms and did not consider how transparency of eligibility criteria can influence the selection of beneficiaries. Using the India Human Development Survey as well as extensive administrative information, we test empirically whether increasing the transparency of eligibility criteria reduces mistargeting. Our empirical results confirm that more transparent eligibility criteria are indeed associated with modestly lower official targeting errors. However, as the described reform of eligibility criteria is an extremely cost-effective measure to improve targeting, we consider the effect relevant. Our results further hold, when we allow for an error band, carefully control for design effects and apply various robustness checks.

Finally in Chapter 5, I turn my attention to unintended behavioral effects. The poverty-reducing impact of social pensions could be constrained if social pension receipt induces working age children who traditionally supported the elderly parent to move out. Living with working-age children can be seen as one relevant proxy of informal support. Using panel survey data, I track a sample of elderly individuals to examine how social pension receipt affects their coresidence with own working age children. Addressing endogeneity concerns with state specific eligibility rules, the empirical results suggest that receiving social pensions reduces the likelihood of living with working age sons. This chapter shows the importance of considering unintended behavioral responses of other household members for the future design of reforms, to further reduce old-age poverty in developing countries like India.

The empirical results of the presented quantitative analyses have concrete policy implications: First, there is an urgent need to reform the targeting of social pensions as the majority of elderly poor continues to be excluded from the benefits and more than 40 percent of non-poor or too young individuals receive the benefits. Using the BPL card for targeting does not really help to improve targeting as the BPL card itself is only weakly targeted towards the poor. In line with recent literature, the results of the first chapter support a reform of the allocation of BPL cards and alternative targeting approaches such as the use of clear exclusion criteria that at least prevent clearly non-poor elderly from accessing the benefits. Second, making eligibility criteria more transparent can indeed play a role to reduce under-coverage of social pension benefits. However, reforms should not stop at this point. First, substantial targeting error remains once the more transparent criteria have been introduced, even according to official criteria, and second, criteria need to be well defined to match the intended target group. Otherwise, there may be no formal targeting error, but nevertheless, the individuals most in need of social protection may not be reached. Consequently, easy to follow and clear-cut exclusion criteria that prevent clearly non-poor individuals from accessing social transfers seem to be the best option for social pensions in India. Third, as social pension amounts are low and elderly individuals typically also depend on the private support provided by their family members, any reform that addresses benefits for the elderly should take into account potential unintended behavioral responses of family members, and more specifically of coresiding working age children. The empirical analysis showed that receiving social pensions reduces the likelihood of living with working age sons. Policy-makers hence need to consider carefully whether reforming social pensions in the future could either incentivize a continuation of the private support or account for the living arrangement of the elderly person.

The presented empirical analyses show important avenues for future research. What remains uncovered in this dissertation is the more general problem that local level implementation deviates from the social policy design at the state or national level. As mentioned above, in the Indian context, social pensions are designed and funded centrally by the national government and complemented in many states by state level social pension scheme. The implementation is carried out by local governments at the panchayat and municipality level. Local government officials deviate from the national or state guidelines for several reasons which finally affects the targeting performance and the effectiveness more generally. In this regard, it will be relevant to examine the discrepancies between the national design and local level implementation on the demand and supply side. While the India Human Development Survey provides some information on the demand side, it is unfortunately not suitable to examine the underlying factors explaining these discrepancies on the supply side.

The last chapter suggests another important but unanswered question on informal support as coresidence with working age children is only a very coarse proxy. Using more detailed data on inter-generational support will be an important step for future research. Similarly, with sons leaving the household, at first sight the elderly seem to be worse off, however the overall welfare effects of this increased mobility need to be taken into consideration as well. Possibly, sons leave the household for better employment opportunities and in the long-run can compensate financially for their absence. These are important questions that remain to be investigated and this dissertation provides relevant insights to be taken into consideration for future research in this area.

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